ABSTRACT

Title of Dissertation: DUAL WATER QUALITY RESPONSES AFTER MORE THAN 30 YEARS OF AGRICULTURAL MANAGEMENT PRACTICES IN THE RURAL HEADWATERS OF THE CHOPTANK RIVER BASIN IN THE CHESAPEAKE BAY WATERSHED

Keota Silaphone, Doctor of Philosophy, 2023

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Eutrophication is the water quality response to over-enrichment by nitrogen (N) and phosphorus (P) in fresh, estuarine, and coastal waters globally. Agricultural best management practices (BMPs) are the primary tool for controlling eutrophication in rural areas, particularly in the Chesapeake Bay watershed, where BMPs are vital to achieving TMDL goals. However, despite the application of BMPs, local water quality in the headwaters of the Choptank River, a major tributary of the Chesapeake Bay on the Delmarva Peninsula, has not improved. Thus, further investigation of agricultural BMP impacts on water quality in the Greensboro watershed is needed. My overarching research question is, “Why have N and P concentrations increased at the USGS Greensboro gauge if agricultural Best Management Practices (BMPs) have been implemented?” I applied statistical approaches to three linked, testable hypotheses to systematically evaluate agricultural BMPs and their impacts on nutrient (N and P) export from the Greensboro watershed.

My first hypothesis was that agricultural BMPs have increased significantly in the Greensboro watershed. To test this hypothesis, I obtained publicly available modeling data via the Chesapeake Assessment Scenario Tool (CAST) and estimated the subsequent edge-of-stream N and P export. My findings indicated that the number of BMPs in the agricultural sector increased significantly between 1985 and 2021, supporting the hypothesis. Overall, modeled agricultural N and P export significantly decreased between 2010 and 2021 ($p < 0.001$). However, the modeled edge-of-stream agricultural nutrient export resulted in no significant change in N export and an increase of 3% in agricultural P export resulting from BMP implementation levels in 2021 compared to 2010. This study demonstrated the use of CAST to acquire reported BMP implementation levels and increased nutrient inputs into the Greensboro watershed between 1985 and 2021. The watershed nutrient inputs mirror the upward trends in N and P export captured by the USGS long-term monitoring station at Greensboro. With this improved access to BMP implementation and nutrient data, decision-makers can consider adaptive management measures to decrease nutrient export downstream.

My second hypothesis was that agricultural BMPs have an adequate basis for estimating their capacity to reduce N export. To test this hypothesis, I conducted a meta-analysis on 689 cover crop N efficiencies reported in 18 empirical and modeling studies. The cover crop N efficiency was calculated as the ratio of an N interception by cover crop biomass or a reduction in soil or groundwater N divided by an N input, e.g., previous spring fertilizer or a previous soil or groundwater N concentration or flux. These variable approaches resulted in wide ranges in mean cover crop N efficiency (10-80%) due to empirical and modeling experimental approaches, varying methods, and parameters used to calculate efficiency. The modeling approach generally resulted in N efficiency values significantly higher than the empirical approach, as did the parallel control-treatment experiments compared to the sequential before-and-after implementation method. Because of these variables, there appears to be no standard methodology to report the effects of cover crops or standardized metadata describing the variables used in the N efficiency calculations. I suggest a standard methodology and metadata that should accompany future reports of cover crop N efficiencies to improve the modeled effects of BMPs on nutrient export.

My third hypothesis was that three methods of estimating N and P concentrations and yields are in agreement and show a relationship to BMP implementation in the Greensboro watershed. To test this hypothesis, I compiled annual nutrient (N and P) datasets based on (1) USGS field measurements of concentrations and discharge, (2) USGS flow-normalized weighted regression based on time, discharge, and season (WRTDS) of concentrations and yields, and (3) CAST-modeled nutrient yields. Statistical analyses revealed time, discharge, agricultural BMPs, and animal waste management practice trends of the three methods. Results indicated that the USGS field measurements and WRTDS flow-normalization methods consistently showed an increase in N and P concentrations and yields. In contrast, all CAST-modeled regressions showed significantly decreasing nutrient concentrations and yields ($p \leq 0.05$), which did not support the hypothesis that all three methods are in agreement. Despite CAST-modeled results decreasing with increasing BMPs, which supports the hypothesis that N and P concentrations and yields show a relationship with BMP implementation, USGS methods resulted in increasing nutrient concentrations and trends. These results indicated significant underestimates of modeled N and P export by CAST. I recommend using adjusted BMP efficiencies during cultural and structural BMP lifespans to improve model outputs. I also suggest two approaches to reflect the role of annual poultry manure applications: (1) model nutrient transport via artificial drainage ditches that interfere with natural nutrient flow pathways and exacerbate N and P transport, and (2) model the accumulation of soil-P and saturated soil-P, resulting in increases in dissolved P and particulate P in downstream surface waters. Agronomic recommendations include developing efficient manure recycling approaches within the local agricultural systems via nutrient management practices and concurrent research and development to support alternative uses of animal waste, including composting, bioenergy generation, granulating/pelletizing, and establishing a marketplace to support the sale of these products and to offset the costs of transporting manure from areas of manure surplus to manure deficit areas.

This dissertation revealed that modeling studies overestimate cover crop N efficiencies in the United States Coastal Plain province and that CAST modeling is not in agreement with the USGS field measurements. CAST-modeled nutrient concentrations and yields decrease over time, indicating improvements in water quality. In contrast, USGS methods consistently show that nutrient concentrations and yields increase, indicating that BMPs are insufficient, inadequate, overwhelmed by nutrient inputs, or efficiencies are overestimated. Indeed, nutrient-reducing BMPs have increased between 1985 and 2021. With over 35 years of BMP implementation, measurable water quality response is expected. However, BMPs that relocate and apply higher amounts of manure annually have also increased with nutrient-reducing BMPs. Rising manure application rates combined with higher fertilizer application rates due to economic pressures on farmers to increase crop yields appeared to have overwhelmed implemented BMPs. Continued manure applications onto croplands in the Greensboro watershed suggest nutrient export will continue to rise; thus, reaching water quality goals is unlikely.

DUAL WATER QUALITY RESPONSES AFTER MORE THAN 30 YEARS OF AGRICULTURAL MANAGEMENT PRACTICES IN THE RURAL HEADWATERS OF THE CHOPTANK RIVER BASIN IN THE CHESAPEAKE BAY WATERSHED

by

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Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park, in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2023

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Dedication

To my loved ones who supported me during my 13-year doctoral journey,

but didn’t see the end result.

To my supportive mother-in-law, Donna M. Wilson, 1944 – 2021.

To my loving fur babies: Sneaky the Butt, Mattie, Baby Blue, and Callie.

To my father, who was a teacher in Laos, and was taken from our family when I was just a baby.

To future generations, there’s always hope, but hope is not a strategy.

Learn lessons from the past.

Act on facts and knowledge, not conjecture.

Trust in science.

Acknowledgments

When I decided to get back into academia, I had no idea what that journey would entail. Before my 12-year tenure at Salisbury University, I was working as a planner at Worcester County Government, where then Planning Director Sandy Coyman had hired me nearly a decade earlier to help safeguard the county's strong agricultural zoning and to carve a path forward for TMDL implementation. My time there taught me that science has little value if elected leaders are unable or unwilling to apply it.

That frustration led me back to school where I could further my education and someday make it my life's work to teach the next generation not to make the mistakes of the current one. While I was still working at the county, Sandy risked his own job to let me take several hours off a week to attend required calculus and chemistry courses for my PhD. I am forever grateful to this man who took a chance on a recent graduate student from Ohio, brought me to Maryland, and shaped my life into what it is today.

Soon after that, and unexpectedly, Henson School of Science Dean Mike Scott, on my dissertation committee, offered me a full-time lecturer position in the Department of Geography and Geoscience (DOGG) at Salisbury University. I'm unsure what compelled him to do so, but this act and his mentoring have changed my life.

In addition to Mike, my entire supportive dissertation committee deserves a tremendous amount of credit for sticking with me during this arduous journey. I've learned so much from each of them–I never knew I loved R coding, and I would have loved to create an entire dissertation based on image collections from IAN. I got so many interesting insights from Slava Lyubchich, and Bill Dennison, to name a few.

A shout-out also goes to my supportive friends and colleagues within the Department. I have been a full-time teacher in the DOGG since 2012, which required part-time doctoral studies and an unconventional journey. But through this, my colleagues were among the most supportive and motivating to be around. They have inspired me to be my best, to set the best example I can, and to take command of the situation.

Hang Nguyen, Valerie Bonhomme, and Tim Canty in the MEES office do so much for the graduate students, and Hang especially has helped facilitate a lot of the administrative work. Their contributions should not go unnoticed.

John Rhoderick (MDA), John Sheppard (SCD), Jim Lewis (Extension), Olivia Devereux (USDA), Rich Batiuk (former committee member), and Alicia Mulkey (MDA) provided a tremendous amount of data without which this research would be a mere nursery rhyme.

At home, my loving and supportive husband, Dave, has been with me since day one of my doctoral journey and has always known I could do this. I was cranky, forgetful, aloof, and he just stayed there by my side. I'm not sure how I got so lucky to have him in my life, but every day, I'm thankful to love him and call him my husband.

My family has been truly supportive and understanding. Time with them is so precious, yet after 10-hour drives to or from Cincinnati during our bi-annual visits, our time was invariably truncated with research, data crunching, writing, and conference calls. They never once complained about the diversion.

Outside of my relatives, my close friends checked in with me regularly as I isolated myself from the world to work on my dissertation. Thanks go to them for caring, giving me the glimpses into the real world when I desperately needed the break, and for simply being good friends.

Most significantly, no words will ever appropriately express my gratitude to Tom Fisher, my advisor. I do not know how many drafts of this tome he read, but it's in the thousands of pages. He possesses unparalleled patience, energy, and optimism. I learned so much from him, especially statistics and SigmaPlot, without which this research wouldn't exist. He's attempted to read my drafts while sailing the Chesapeake Bay, attending his daughter's wedding in Utah, vacationing overseas in Europe, and recovering from a stroke. His value to both me personally and society is incalculable.

With patience and kindness from the people above, I made it through my husband's very serious nasal cancer, a global pandemic, and the loss of my mother-in-law just in the past five years. Dissertations are not the stuff of individuals but teams like this one, making our world more livable and better understood.

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Chapter 1: Land use management practices: a global response strategy to anthropogenic eutrophication

1.1 Eutrophication

Eutrophication is a well-documented water quality response to over-enrichment by nitrogen (N) and phosphorus (P) in fresh, estuarine, and coastal waters from nonpoint sources and point sources (Boesch 2001; Kennish 2002; Kemp et al. 2005; Howarth 2008; Schindler et al. 2008; Smith et al. 2009; Lankoski et al. 2013; Foucher et al. 2020; Malone et al. 2020). Atmospheric N deposition over a water source, stormwater from populated areas <100,000, and agricultural runoff from croplands, pasture, and range are examples of nonpoint sources that are difficult to reduce due to their diffuse nature (Carpenter et al. 1998; D'Arcy et al. 2001; Reay 2004). Moreover, controlling point sources, such as sewage effluent discharge points to aquatic systems, has become increasingly difficult in developing and industrializing regions of the world (Carpenter et al. 1998; Jayme-Torres et al. 2018; Boesch 2019; Wang et al. 2019; Malone et al. 2020; Neher et al. 2021). Nonpoint and point sources of N and P have contributed to frequent instances of eutrophication, yet controlling these pollution sources remains a global challenge.

Consequences of over-enrichment by N and P include (1) increased phytoplankton biomass and algal blooms, (2) high rates of decomposition of organic matter in bottom waters, (3) hypoxia or anoxia, and (4) decreased sunlight reaching shallow-water submerged aquatic vegetation (Carpenter et al. 1998; Boesch 2001; Paerl et al. 2002; Daigle 2003; Kemp et al. 2005; Canfield et al. 2010; Boesch 2019). Consequently, the toxic algal blooms can cause foul odors, bad tastes, fish lesions, fish kills, and neurological disorders in humans (Smil 2000; Boesch 2001; Burkholder et al. 2001; Glibert et al. 2001; Paerl et al. 2002; Funari et al. 2008;

Bate et al. 2019). Additionally, eutrophication in Lake Erie ultimately led to the Toledo water crisis in 2014, which prevented more than 400,000 residents from using their domestic water supply for three days (Jetoo et al. 2015).

However, controlling dissolved inorganic N and P from nonpoint sources and point sources originating from urban and agricultural land uses can limit phytoplankton growth. Phosphorus often limits phytoplankton growth in freshwater, while nitrogen is often the limiting nutrient in saltwater. Thus, P limitation is predominant in the upper reaches of estuaries, where freshwater tributaries enter the estuary and decrease with increasing salinity, where the estuary and ocean meet (Jordan et al. 2008). In addition, Fisher et al. (1999) have shown the relative abundance of N and P can also change with seasons. Winter N limitation resulted from dissolved inorganic N depletion at high salinity stations before spring groundwater nitrate delivery. The reaeration of bottom sediments at lower salinity stations likely caused fall P limitation.

1.2 Adverse impacts of anthropogenic land uses

Studies have shown anthropogenic land-use activities contribute to coastal eutrophication globally (Carpenter et al. 1998; Howarth 2004; Foley et al. 2011; Majumdar et al. 2013; Boesch 2019; Malone et al. 2020). The densely populated coastal regions of the Black Sea (Fabry et al. 1993; Mikaelyan et al. 2013), South China Sea (Ding et al. 2016), and East China Sea (Chen et al. 2016) have contributed to persistent coastal eutrophication since the mid-1900s. Urban orthophosphate sources from wastewater treatment plants and agricultural sources of total nitrogen and nitrate loads have increased coastal eutrophication and stressed the freshwater and marine ecosystems of the Mediterranean region (Ærtebjerg et al. 2001; Viaroli et al. 2014; Malago et al. 2019). Additionally, inland agricultural land uses and riverine wastewater discharges increased N input to the eastern China seas (Zhang et al. 2010; Liang et al. 2016; Wang et al. 2021), the Atlantic coastal zones of the United States, and the Gulf of Mexico (Rothenberger et al. 2009; Oelsner et al. 2019; Rabalais et al. 2019).

The combined effects of increasing urban and agricultural activities during the latter half of the 20th century in Europe and North America accelerated atmospheric N deposition locally (Paerl et al. 2002; Lintern et al. 2018) and threatened pristine areas downwind of anthropogenic emissions, including the Arctic Tundra (Choudhary et al. 2016) and forest ecosystems of Europe, China, and North America (Zhu et al. 2015; Dirnböck et al. 2020). Between 1980 and 2003, nitrogen oxide (NO_x) emissions from inland agricultural regions and urban power plants, industry, and transportation (Ohara et al. 2007) in China increased atmospheric N deposition to the East China Sea and the South China Sea to levels slightly less than the total N input from riverine discharges and wastewater effluent (Zhang et al. 2010; Liang et al. 2016). During the late 1990s, fossil fuel combustion was the largest source of NO_x emissions in the United States and accounted for approximately 10-40% of new N loading to estuaries along the East Coast and the Gulf of Mexico (Paerl et al. 2002; Driscoll et al. 2003). However, the Clean Air Act has decreased emissions and deposition of oxidized N in the Northeast of the United States and the Chesapeake Bay watershed (Gilliam et al. 2019; Zhang et al. 2023).

Intensive animal operations have historically contributed to atmospheric N emissions and subsequent deposition onto land. For example, the growth and intensification of poultry, swine, and cattle operations in the United States Midwest and Mid-Atlantic regions and Western Europe increased ammonium (NH_4^+) emissions and land and water deposition. (Paerl et al. 2002). Recent studies draw strong relationships between intensive animal operations and increased atmospheric N emissions and deposition. For example, Baker et al. (2020) estimate ammonia deposition of 11,100 Megagrama yr^{-1} (10,600 Mg yr^{-1} deposition to land, and 508 Mg yr^{-1} deposition to water (1 Mg = 1,000,000 g = 1.1023 US Tons)) on the Maryland Eastern Shore and the Chesapeake Bay from poultry operations on Maryland's Eastern Shore. In addition, model simulations indicate that over 70% of ammonia (NH_3) emissions are deposited near the poultry operations, which are transported via drainage ditches and surface waterways to the Chesapeake Bay (Baker et al. 2020). Similarly, Yi et al. (2021) found NH_3 emitted from intensive pig farms in China deposited near the emission source, and Shen et al. (2016) found that intensive cattle feedlots are large NH_3 emission sources and that NH_3 deposition around feedlots is a significant nitrogen input in Victoria, Australia. Moreover, regions naturally prone to hypoxia, such as the Baltic Sea, have experienced increased hypoxia over the past century primarily due to excessive nutrients from agriculture (Svanback et al. 2019) and atmospheric deposition (Elofsson 2010; Carstensen et al. 2019).

1.3 Management practices for nonpoint sources

Today, agricultural best management practices (BMPs) are the primary tool for controlling eutrophication in rural areas. There are two major categories of agricultural BMPs: structural and cultural. Examples of structural BMPs include the maintenance and construction of riparian zones, swales, bioretention cells, filter/buffer strips, stream fencing, catch basin inserts, manure lagoons, terraces, wetlands, weirs, dry detention ponds, and sediment control basins (USEPA 2002, 2003; Cullum et al. 2006; Makarewicz et al. 2009). Cultural or non-structural agricultural BMPs include rotational grazing, land conversion, cropping rotation, soil testing, cover crops, tillage practices, management of nutrients, soil, pests, and residue, and timing manure spreading (USEPA 2003; Cullum et al. 2006; Makarewicz et al. 2009).

Some BMPs target either N or P releases. Thus, the choice of BMPs may depend on which element is limiting phytoplankton growth. For example, anthropogenic inputs from sewage treatment, agriculture, or releases of nitrogen oxides or ammonia into the atmosphere can also alter the relative abundance of N and P in aquatic ecosystems (Jordan et al. 2018). Hartzell et al. (2017) found high concentrations of P in Gunston Cove sediments when the sewage treatment plant discharged P in the mid-1970s. They then sharply decreased in the late 1970s and early 1980s following wastewater treatment plant upgrades removing P from effluent.

Management practices can function as loss prevention or end-of-pipe treatments to capture lost N and P. Loss prevention BMPs stop pollutants from leaving the soil and include BMP practices such as cover crops, low nitrogen fertilizer, filter strips and grass waterways, no-tillage, and nitrification inhibitors (Inamdar et al. 2001; Rosolem et al. 2017; Higgins et al. 2019; Restovich et al. 2019; Hively et al. 2020). Many other BMPs, such as drainage ditch management practices (bioreactors, control structures, weirs, and vegetated ditches), sediment ponds, and constructed wetlands, function as end-of-pipe BMPs that attempt to remove or reduce pollutants already moving from the agroecosystem (USEPA 2002; Christianson et al. 2017a; Jones et al. 2017; Wang et al. 2017b; Faust et al. 2018; Kumwimba et al. 2018; Mittelstet et al. 2019; Crumpton et al. 2020).

Agricultural BMPs include policies and regulations, agronomic practices, maintenance procedures, and management activities that are considered to reduce nutrient export and nonpoint source pollution impacts on surface waters (USEPA 1993a, 1993b; Anderson et al. 1995; Edwards et al. 2015; Haas et al. 2017; Pearce et al. 2017; Jain et al. 2019; Restovich et al. 2019). However, mandatory and voluntary actions have limited nutrient inputs from nonpoint sources and point sources by varying degrees. Regulatory and technology improvements have demonstrated quantifiable nutrient reductions from point source discharges such as wastewater treatment plants (Boesch 2001; Polprasert 2004; Ruhl et al. 2010; Sattayatewa 2010; Vymazal 2010; Kleemann et al. 2015; Boesch 2019). Early voluntary actions have had limited success in lessening nutrient loads, specifically in rural areas where agriculture is the dominant land use (CBP 1983, 1987, 2000; Reimer et al. 2012; Drevno 2016; Marks et al. 2019).

Agricultural BMPs are not distributed equally across the globe. Due to more agricultural intensification in industrializing nations, more BMP implementation occurs in the United States (Lowrance et al. 1997; Mitsch et al. 2000; Stone et al. 2004; Johnson et al. 2013; Crumpton et al. 2020), China (Liu et al. 2013; Sun et al. 2013), Australia (Thorburn et al. 2013), Canada (Holmes et al. 2016), and Europe (Balestrini et al. 2011; Christen et al. 2013). An example of using BMPs is the attempt to improve water quality in the Chesapeake Bay, the largest estuary in North America. The United States Environmental Protection Agency (USEPA), state environmental agencies, and the United States Department of Agriculture (USDA) have advocated the use of agricultural BMPs and have increased BMP implementation across the Chesapeake Bay watershed (Boesch 2006; Sutton et al. 2009; Fanelli et al. 2019; Harding et al. 2019; Sekellick et al. 2019; Ator et al. 2020; Hively et al. 2020). After the Chesapeake Bay total maximum daily load (TMDL) was approved by USEPA in December 2010, agricultural BMP implementation nearly doubled between 2010 and 2014 in the bay watershed due to increased applications of precision rotation grazing, precision agriculture, land retirement, and cover crops (NRC 2011; Hanson 2018; Sekellick et al. 2019). The Bay TMDL established a “pollution diet” that prescribed annual pollution limits for the Chesapeake Bay and its tributaries to meet a national goal of swimmable and fishable waters (USEPA 2010b). In addition to the watershed BMP implementation, the nation-scale policy implementation of the Clean Air Act led to decreased emissions and subsequently decreased regional N atmospheric deposition (Eshleman et al. 2013; Fisher et al. 2021), which has also been reported within areas of the Chesapeake Bay watershed such as the Choptank River Basin and Upper Potomac River Basin (Eshleman et al. 2016; Gilliam et al. 2019; Fisher et al. 2021). In response to decreased atmospheric N deposition, surface water quality improved in the Upper Potomac River (Eshleman et al. 2013; Eshleman et al. 2016) and elsewhere (Fisher et al. 2021).

Despite widespread implementation of best management practices across the Chesapeake Bay watershed, P load reductions have been inconsistent, and dissolved P loads have increased in several tributaries, including the Choptank River in Delmarva (Kleinman et al. 2019; Fisher et al. 2021). During a time when BMP implementation increased (McCarty et al. 2008; Fox et al. 2021) and atmospheric N deposition decreased (Fisher et al. 2021), the water quality should have improved in the headwaters of the Choptank River (Hively et al. 2020). Thus, further investigation of agricultural BMP impacts on water quality in the watersheds of the Choptank River Basin is needed.

The United States Geological Survey (USGS) gauging station near Greensboro, Maryland, monitors the largest gauged watershed in the Choptank River Basin (Fig. 1.1). The watershed encompasses 303 km^2 of the Choptank River headwater (Fig. 1.2). Land cover has remained relatively stable since 1950 and is dominated by forests, forested wetlands, and other natural resources (50%) and agriculture (47%) (Fisher et al. 2006a; CBP 2020b). Rural development (3%) comprises the remaining land cover in the watershed. However, the intensification of agricultural land use results from increasing fertilizer applications to crop fields and large-scale poultry operations (Fisher et al. 2006a; Fisher et al. 2010; USEPA 2010c; Kleinman et al. 2019). The long-term water quality record at the Greensboro gauge in an agricultural landscape has been the subject of numerous water quality and agricultural nutrient and BMP studies (Hively et al. 2011; Nino de Guzman et al. 2012; Denver et al. 2014; McCarty et al. 2014; Ator et al. 2015; Zhang et al. 2015a; Moyer et al. 2018; Fisher et al. 2021).

The Greensboro watershed has been monitored by the USGS at the Choptank River since 1948 for hydrology and 1965 for water quality and is the only river input monitoring (RIM) station on the Delmarva Peninsula. Nine RIM watersheds are monitored for nutrient and sediment concentrations, representing nearly 80% of the delivered load to the Chesapeake Bay (Moyer 2016). Additional water quality monitoring in the Greensboro watershed is conducted by the Delaware Department of Natural Resources and Environmental Control (DNREC) and the University of Maryland Center for Environmental Science (UMCES) (DNREC 2019; Fisher et al. 2021).

Although agricultural BMP implementation has occurred in the Choptank River Basin, water quality is degrading in its headwaters (Hirsch et al. 2010; Langland et al. 2012; Zhang et al. 2015a). The USGS long-term water quality record indicates an overall increase in TN and TP (Fisher et al. 2021, Fig. 1.3). Increasing TN and TP in the non-tidal portion of the Choptank River is reason for concern due to nutrient levels approaching the nutrient criteria of 2.5 mg TN L^{-1} and currently exceed the nutrient criteria of 0.094 mg TP L^{-1} for healthy streams in Maryland (Morgan et al. 2013). Two-thirds of the headwaters lie in Delaware, and the nutrient threshold values in Delaware are 3.0 mg TN L^{-1} and 0.2 mg P L^{-1} (DNREC 2005). The long-term record also shows brief interannual variability in N and P concentrations. Detectable fluctuations in nutrient concentration over the long-term water quality record may indicate a possibility of events, or a singular event, that may have influenced water quality.

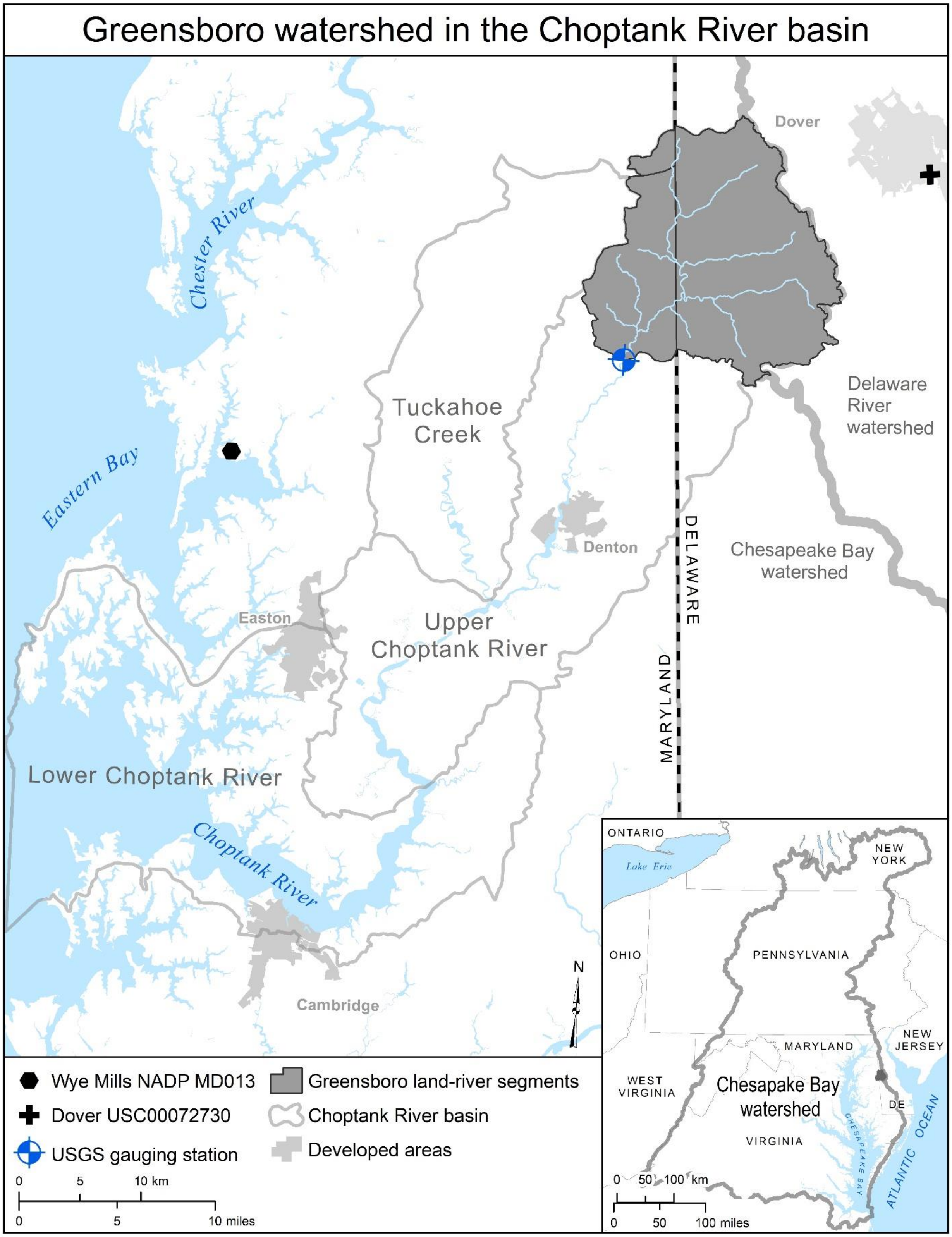


Figure 1.1. The Choptank River basin encompasses the headwaters of the Choptank River basin on the Delmarva Peninsula in the Chesapeake Bay watershed.

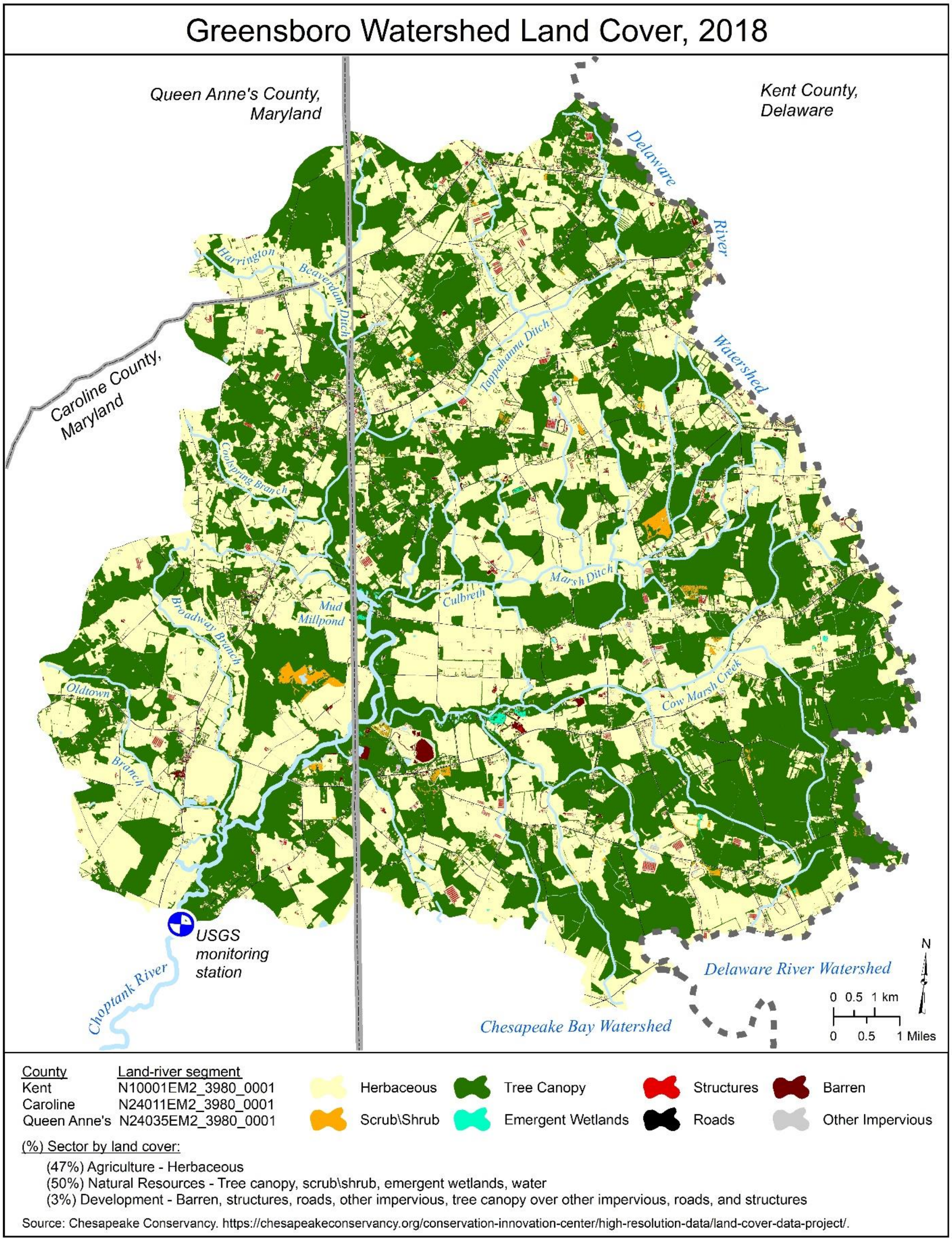


Figure 1.2. Greensboro watershed land cover map.

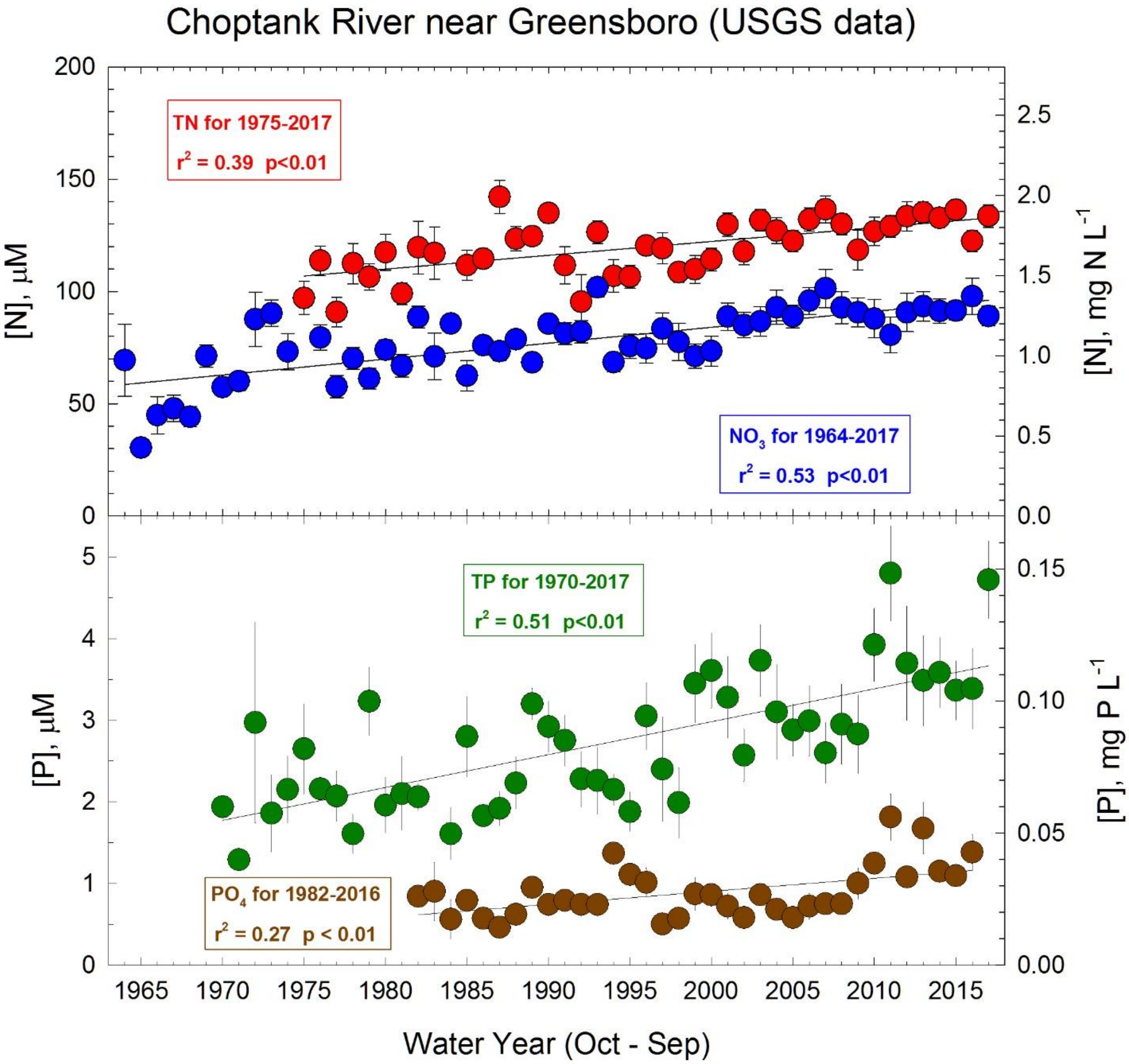


Figure 1.3. Interannual trends in N and P concentrations at the Greensboro USGS gauging station in the Choptank River headwater (Fisher, pers. com.).

1.4 Research focus

My research investigates why N and P concentrations have increased at the USGS Greensboro gauge if the agricultural sector implemented best management practices (BMPs). The long-term water quality record indicates that one or more of the following is true:

(1) There is insufficient BMP implementation (Mulla et al. 2005; Sutton et al. 2010; Kroll et al. 2019),

(2) Inadequate maintenance led to malfunctioning BMPs (Mulla et al. 2005; Sutton et al. 2010; Rittenburg et al. 2015; Lintern et al. 2020),

(3) BMPs are overwhelmed by anthropogenic N and P inputs (Fisher et al. 2021),

(4) BMP effects are masked by legacy nutrients or nutrient time lags (Tesoriero et al. 2009; Sharpley et al. 2013; Van Meter et al. 2016; Vero et al. 2017),

(5) The N and P efficiencies are overestimated (Simpson et al. 2009).

My research examines the above possibilities and is guided by an overarching question: "Why have N and P concentrations increased at the USGS Greensboro gauge if agricultural Best Management Practices (BMPs) have been implemented?” To test the overarching research question, I attempt to relate changes in water quality to agricultural BMP effectiveness in the Greensboro watershed. An investigation of three linked, testable hypotheses evaluates the overarching research question. Below is a chapter outline of my dissertation and each testable hypothesis.

Chapter 2. The primary hypothesis of Chapter 2 is that agricultural best management practices (BMP) have increased significantly in the Greensboro watershed from 1985 to 2021. Test of hypothesis 1 quantifies the long-term agricultural BMP implementation efforts and the estimated nutrient reduction impact in the Greensboro watershed.

Major research questions addressed are:

1. Have BMPs increased in the Greensboro watershed?
2. What is the expected effect of BMPs in the Greensboro watershed?

Chapter 3. The primary hypothesis of Chapter 3 is that agricultural BMPs have an adequately tested basis for estimating their efficiency in the United States Coastal Plain province. Test of hypothesis 2 assesses the scientific literature on the reported efficiency of agricultural BMPs at the field and watershed scale.

Major research questions addressed are:

1. Is BMP efficiency adequately measured?
2. What are the reported limitations of BMPs?

Chapter 4. The main hypothesis of Chapter 4 is three methods of estimating N and P concentrations and yields are in agreement and show a relationship to BMP implementation in the Greensboro watershed. To test hypothesis 3, I compiled annual nutrient export datasets based on (1) USGS field measurements of concentrations and discharge, (2) a flow-normalized weighted regression based on the time, discharge, and season (WRTDS) approach used by the

United States Geological Survey (USGS), and (3) Chesapeake Assessment Scenario Tool (CAST) modeling.

Major research questions addressed in Chapter 4 are:

1. Have BMPs influenced nutrient concentrations and yields in the Greensboro watershed?
2. Besides BMP implementation, have other factors influenced nutrient concentrations and yields in the Greensboro watershed?

Chapter 5. Lastly, Chapter 5 will provide an interpretive summary of research conclusions and recommendations for future research and policies to improve water quality in the Choptank River and Chesapeake Bay basins.

Chapter 2: The historical implementation of agricultural best management practices in a small rural watershed and expected nutrient export, Chesapeake Bay watershed: 1985-2021

Abstract

Due to insufficient restoration progress from the 1980s through the mid-2000s, persistent poor water quality in the Chesapeake Bay and its tributaries led to one of the United States history's most ambitious regulatory goals, total maximum daily loads (TMDL). Established in December of 2010, the Chesapeake Bay TMDL outlined water quality goals to attain a healthy Bay watershed, and stakeholders would install best management practices (BMP) aimed to reduce total nitrogen (N), total phosphorus (P), and sediment or total suspended solids (TSS) by 2025 to help achieve the TMDL goals. Thus, the primary hypothesis of Chapter 2 is that BMP implementation has increased significantly between 1985 – 2021. To test this hypothesis, I quantified BMP implementation efforts and subsequent nutrient impacts in the Greensboro watershed at the headwaters of the Choptank River on the Delmarva Peninsula using the web-based Chesapeake Assessment Scenario Tool (CAST). The CAST data indicated that the number of BMPs for all sectors increased significantly between 1985 and 2021. However, the overall edge-of-stream nutrient export resulted in no change in N, an increase of 2% in P, and a 14% decrease in TSS from 2010 to 2021. Additionally, the USGS long-term water quality data for the Greensboro watershed shows degrading water quality due to increasing nutrient concentrations (Fanelli et al. 2019; Mason et al. 2021). These results indicate (1) that the increased number of functioning BMPs are overwhelmed by current nutrient inputs to the Greensboro watershed and (2) that there are insufficient quantities of BMPs suited to the natural environment in the watershed, which limits reaching the local TMDL goals of reducing N and P by 24% and 18%,

respectively. This study demonstrated the use of CAST to acquire reported BMP implementation levels and increased nutrient inputs into the Greensboro watershed between 1985 and 2021. The watershed nutrient inputs mirror the upward trends in N and P export captured by the USGS long-term monitoring station at Greensboro. With this improved access to BMP implementation and nutrient data, decision-makers can consider adaptive management measures to decrease nutrient export downstream. These measures may include higher payments to incentivize BMP implementation, more manure management options, such as reducing manure N and P applications onto agricultural cropland, applications of supplemental manure onto alternative vegetative covers outside the agriculture sector, and publicly funded manure transport programs to remove manure from surplus areas to deficit areas, and evaluations of modeled N and P nutrient export.

2.1 Introduction

2.1.1 Regional initiatives

Nonpoint sources from urban and agricultural land uses are the principal impediments to achieving water quality goals throughout the United States, Europe, and China (Macias et al. 2018; Oelsner et al. 2019; Svanback et al. 2019; Zou et al. 2020; Wang et al. 2021). Nonpoint sources are inherently challenging to regulate because of their diffuse discharges. Instead, policymakers rely on voluntary, incentive-based approaches to minimize nonpoint source pollution (Drevno 2016). For example, the Common Agricultural Policy provides the basis for voluntary agricultural nonpoint source policies for European Union member states (Lankoski et al. 2013). Additionally, several European Union Directives prioritize efforts to curtail eutrophication in the coastal seas of Europe by allowing member states to dictate how to proceed (Lankoski et al. 2013). For example, the objective of the 1991 Urban Waste Water Treatment Directive is to protect the environment from adverse effects of urban and certain industrial wastewater discharges. The Nitrates Directive, adopted in 1991, promotes good farming practices to protect ground and surface water quality (Boesch 2019).

Additional examples of voluntary, incentive-based approaches to abate eutrophication include the Lake Erie Binational Phosphorus Reduction Strategy, an agreement between the United States and Canada to reduce total phosphorus by 40% (Annex 2019; Hanief et al. 2019). Efforts to control excess algal growth in the Neuse River and Estuary, North Carolina, began in the 1980s. Still, continued water quality issues led to the development of a Total Maximum Daily Load (TMDL) for nitrogen (N) in 1999 to improve conditions in N-sensitive estuarine waters (Lebo et al. 2012). Recurring poor water quality in the Chesapeake Bay and its tributaries led to one of U.S. history's most ambitious total maximum daily loads (TMDL). In December

2010, the United States Environmental Protection Agency (USEPA) established the Chesapeake Bay TMDL to achieve a national goal of the designated uses of swimmable and fishable waters (USEPA 2010b).

Meeting the prescribed nutrient pollution load allocations for the estuary requires an overall nutrient reduction of 25% total nitrogen (N), 24% total phosphorus (P), and 20% total suspended solids or sediments (TSS) from the modeled 2009 baseline (USEPA 2010a). Smaller nutrient load allocations for land-based (LA), waste load allocation (WLA), and atmospheric deposition combine to form the larger Bay TMDL, summarized in Table 2.1. The annual nutrient load allocations are the allowable nutrient export delivered to tidal waters (USEPA 2010g).

Table 2.1. Chesapeake Bay TMDL. The nutrient load allocations are adapted from USEPA 2010a. These annual load allocations are the allowable nutrient export delivered to tidal waters (USEPA 2010g). The 25% N reduction goal excludes atmospheric N deposition because assurances are high that the federal Clean Air Act (CAA) regulations will decrease N deposition (Eshleman et al. 2016).

Reduction goals	**Unit**	**N**	**P**	**TSS**
Nutrient reduction goal:	%	25	24	20
2009 baseline	kg y^{-1}	113,063,725	7,467,473	3,669,799,883
Bay TMDL	kg y^{-1}	91,453,940	5,689,127	2,927,310,544
Bay TMDL load allocations				
Waste	kg y^{-1}	24,202,929	2,046,727	407,428,818
Land-based	kg y^{-1}	60,129,609	3,642,399	2,519,881,726
Atmospheric deposition	kg y^{-1}	7,121,402	---	---

Coordination among federal, state, and local partners has required demonstrable interim actions be installed by 2025 to meet the TMDL initially, and disinclined jurisdictions could face additional USEPA enforcement (USEPA 2009, 2010f, 2017a, 2018) such as:

- Increase the number of sources, operations, or communities regulated under the NPDES permit program (USEPA 2010a).
- Expand EPA oversight review on federally permitted pollution sources such as wastewater treatment plants (WWTP), municipal separate storm sewer systems (MS4), and large animal agriculture operations (USEPA 2010b).
- Reject inadequate NPDES permits that do not meet the CWA requirements or are inconsistent with the WLA in the Bay TMDL (USEPA 2017b).
- Condition or redirect EPA grant funding based on demonstrated progress that meets watershed implementation plans (WIPs) or yields higher N, P, or TSS reductions (USEPA 2010a).

The cooperative partnership between the EPA, Bay states, and local stakeholders following the TMDL resulted in more coordinated actions designed to meet the TMDL goals.

2.1.2 The impact of best management practices on nonpoint source pollution

Best management practices (BMPs) have been recommended worldwide to limit global eutrophication (Zhuang et al. 2016; Stuart 2017; Queensland 2018; Barao et al. 2019; Xue et al. 2020). One of the earliest BMP initiatives emerged from developing the Clean Water Act in 1948 specifically to address point source pollution (Copeland 2016). Subsequent amendments resulted in the formation of the United States Environmental Protection Agency, the lead agency responsible for implementing the 1972 Federal Water Pollution Control Act, which recommended sediment pollution control systems to improve the aquatic environment. Since the 1970s, countries, including the United States and the United Kingdom, have initiated agricultural nonpoint source controls (Zhuang et al. 2016). In recent years, several in-depth studies of BMPs have been carried out, such as the Conservation Effect Assessment Project in the United States (Moriasi et al. 2020), the Watershed Evaluation of Beneficial Management Practices in Canada (Stuart 2017), and the Baltic Sea Action Plan (Elofsson 2010; Wulff et al. 2014); these projects encouraged the broader applications of BMPs targeting nonpoint source pollution worldwide.

Best management practices (BMP) applied in the rural-urban development and agriculture sectors have been instrumental in intercepting nutrients. However, attributing nutrient reductions and documenting long-term BMP implementation can present unique challenges. For example, in response to the Toledo water crisis (Jetoo et al. 2015), affected jurisdictions in Canada and the United States recognized the need for widespread aggressive agricultural management practices at higher densities (Annex 2019). In turn, Oelsner et al. (2019) found two-thirds of the sediment loads were decreasing in the Great Lakes region. An example in the Chesapeake Bay watershed required WWTP upgrades, which demonstrably reduced nutrient export to the bay tributaries (USEPA 2015; Liner et al. 2017; Oelsner et al. 2019; Fisher et al. 2021), and subsequent amendments to the 1990 Clean Air Act reduced nitrate-N in the Upper Potomac River (Eshleman et al. 2013; Eshleman et al. 2016). In contrast, attempts to reduce agricultural and urban nonpoint source pollution have yielded mixed results (Fanelli et al. 2019; Ator et al. 2020; Fox et al. 2021).

Despite the lack of progress in reducing nonpoint source pollution, much effort has been expended toward that goal. For agricultural nonpoint source pollution, there has been increased state cost-share assistance to implement BMPs such as cover crops combined with federal funds of over a billion dollars in just this past decade for programs such as the Conservation Reserve Enhancement Program (CREP), Environmental Quality Incentives Program (EQIP), Agricultural Conservation Easement Program (ACEP), and Conservation Stewardship Program (CSP) (Wallander et al. 2021). These programs increased participation in the TMDL effort bay-wide (USDA 2014, 2022). In contrast, the increase in enrollment did not achieve already low conservation goals in Maryland, and Pennsylvania's participation levels in the Susquehanna watershed remain among the lowest in the Bay watershed (USEPA 2017b; Surrick 2022). Additionally, voluntary non-funded BMPs remain unaccounted for, but the 2022 Chesapeake Bay State's Partnership Initiative seeks to recognize these voluntary approaches of locally-led conservation practices (USDA 2022). Upgrades to WWTPs have clearly reduced pollution to the Bay (Ruhl et al. 2010; Fisher et al. 2021); however, the impact of BMPs on agricultural nonpoint source pollution is unclear even though participation levels have risen (Fox et al. 2021), and efforts are underway to track voluntary agricultural BMP implementation to accurately portray participation levels in the agricultural sector.

2.1.3 Chesapeake Assessment Scenario Tool (CAST)

Joint efforts between federal, state, and local stakeholders enhanced BMP data quality to understand how conservation practices could improve water quality in the Chesapeake Bay watershed and achieve the N, P, and TSS TMDL goals (Hanson 2018; Hively et al. 2018). For example, as part of the 2010 partnership between the United States Geological Survey (USGS) and the United States Department of Agriculture (USDA), the USGS analyzes the effects of agricultural conservation practices on nutrients and pesticide transport to the Bay using USDA-supplied conservation implementation data. In turn, the USGS aggregates the data to the county and eight-digit hydrologic unit code (HUC) watershed scales to maintain the anonymity of site-specific farm data before releasing the data to the public (Hively et al. 2018). An example of a state-federal data-sharing partnership is the National Environmental Information Exchange Network (NEIEN), where designated agencies within each jurisdiction submit NPS BMP implementation information for inclusion in the Chesapeake Bay watershed Model Phase 6 (Hanson 2018). Streamlining data sharing between multiple agencies has improved data quality and efforts to track BMPs that aim to meet the TMDL goals.

With notable improvements in data sharing and quality, the web-based version of the Bay model, the Chesapeake Assessment Scenario Tool (CAST), disseminated the BMP data via http://cast.chesapeakebay.net/. The web interface also provides in-depth model documentation, and Kaufman et al. (2021) **summarized the CBP modeling framework and CAST online model structure and functions.** The BMP implementation levels and edge-of-stream nutrient loading (nutrient export = areal rate of each land use (kg ha^{-1} y^{-1}) x area (ha)) scenarios in the Chesapeake Bay watershed are publicly available at no cost and have been a source of BMP implementation data for the CBP Integrated Trends Analysis Team (CBP 2021). CAST also added transparency to ongoing efforts to reach the TMDL goals by permitting users to run scenarios that quantify the subsequent effect on time-averaged export of nutrients (N, P, and TSS) in the Chesapeake Bay watershed (CBP 2020c). The time-averaged nutrient outcomes represent the hydrologic average of current or future watershed conditions (CBP 2020a). An example of a practical application of the CAST time-averaged nutrient estimates is local jurisdictions vying for grant funds that require reports of the quantitative effect of proposed BMP projects on nutrient export (Mitchell 2023). An improved BMP data-sharing policy among stakeholders enhanced publicly available information via CAST while simultaneously allowing stakeholders to understand the estimated water quality response to BMP implementation scenarios in the Chesapeake Bay watershed.

2.1.4 Empirical and modeling nutrient export

Efforts to monitor water quality due to land management practices are performed via empirical research and modeling. Empirical studies have demonstrated that agricultural BMPs can reduce nutrient export from croplands at small spatial scales (Christianson et al. 2017a; Rosen et al. 2017; Hirsh et al. 2021; Lucas et al. 2021). If enough BMPs are installed and maintained, then the cumulative effect of BMP implementation should decrease watershed nutrient export concurrent with a growing population, increased development, and more intensive agricultural land uses, as shown by Roberts et al. (2009) and Miller et al. (2019) in modeling studies. In the Chesapeake Bay watershed model, steps taken to minimize uncertainty include the amount of data and resources used to develop, calibrate, and verify the accuracy of each of the Bay models (USEPA 2010d). Additional BMP and agricultural data that affect nutrient export were compiled and considered in the bay model, including agricultural areas and the spatial distribution and types of agricultural lands (croplands, pastures, etc.), fertilizer application rates, livestock populations, and the locations of riparian buffers and wetlands that may supplement watershed monitoring results (Weller et al. 2010). However, a known limitation of the Bay model is that the nutrient components do not consider lag time (Sanford et al. 2013). Due to the complexity of the Chesapeake Bay model, a thorough assessment of model prediction uncertainty is unlikely (NRC 2011). Multiple models simulating the airshed, land use, watershed, and estuary have been recommended for the Bay restoration effort to strengthen the use of the model predictions (Weller et al. 2013). By combining model predictions into a model average, the overall reliability and predictions may be improved and could help describe uncertainty (Boomer et al. 2013).

2.1.5 Research purpose

As the 2025 TMDL deadline nears, an in-depth assessment of credited BMPs reported by CAST is needed to understand the influence of the TMDL on BMP implementation and overall BMP effectiveness. For my research case study, I examined the historical BMP record available via CAST to estimate the impact of the Bay TMDL in the Greensboro watershed. The advantage of using CAST is being a single-source data repository of historical BMP implementation, which state agencies have submitted, verified by the EPA, and is publicly available at no cost. The BMP data are also downloadable based on predefined geographic spatial scales, and anyone can generate BMP implementation scenarios using the CAST web interface at http://cast.chesapeakebay.net/. Via CAST, users can also obtain detailed reports summarizing the level of BMPs credited and submitted and resulting nutrient export by *progress year*, which begins July 1 and ends the following (progress) year on June 30.

The primary hypothesis of Chapter 2 is BMP implementation has increased significantly in the Greensboro watershed between 1985 and 2021. The test of hypothesis 1 quantifies the long-term BMP implementation efforts and subsequently estimates the nutrient reduction impact in the Greensboro watershed. The major research questions addressed are:

1. Have BMPs increased in the Greensboro watershed?
2. What is the expected effect of BMPs in the Greensboro watershed?

2.2 Methods

2.2.1 Study site: Greensboro watershed

The Greensboro watershed (304 km^2) encompasses the non-tidal portion of the Choptank River, located on the Delmarva Peninsula in the Coastal Plain Region of the Chesapeake Bay watershed (Fig. 2.1). The watershed has a humid, temperate climate with average precipitation (progress years 1985 – 2021) of 1166 mm y^{-1} and large interannual variability ranging from 756 mm in 2021 to 1654 mm in 2019 (NCEI-NOAA 2023). Forests and wetlands (50%) dominate the watershed due to primarily forested wet soils unsuitable for farming or housing (Fisher et al. 2010). The remaining (47%) is agricultural land cover, and less than 4% is rural development. Over two-thirds of the watershed (211.5 km^2) is in Kent County, Delaware, and two Maryland counties, Queen Anne's (7.5 km^2) and Caroline (85 km^2), comprise the remaining third. Soil types include predominantly poorly drained to well-drained soils with a moderately permeable subsoil of either clay loam to sandy loam or sandy loam to sandy clay loam (DNREC 2005). Within the non-tidal region, hydric soils comprise 79% of the land area within the Greensboro watershed. The elevation in the Greensboro watershed typically ranges from 9-23 meters; however, due to the Sandtown Landfill (barren land cover designation located ~ 1.5 km east of the state line just south of the Cow Marsh Creek), the highest point in the Greensboro watershed is 57-58. The watershed drains approximately 15% of the Choptank River Basin comprised of the northern tidal fresh TMDL segment (CHOTF) draining into the southern tidal portion of the basin.

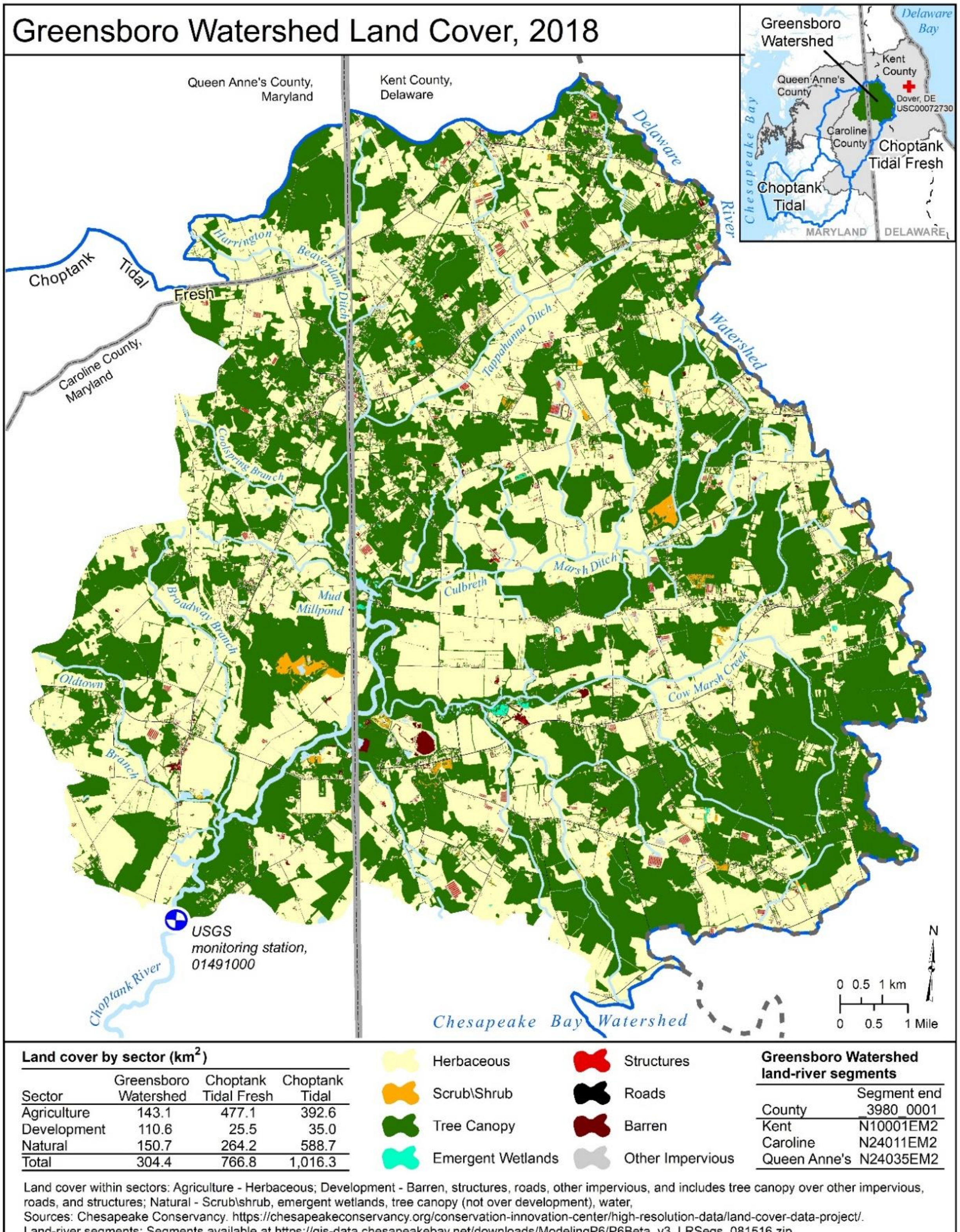


Figure 2.1. The Greensboro watershed (304 km^2) is dominated by forests and wetlands (50%) and agricultural land (47%) and is the only USGS river input monitoring watershed located on the Delmarva Peninsula. The watershed drains 28% of the Choptank Tidal Fresh segment and 15% of the entire Choptank River Basin.

2.2.2 River input monitoring watersheds

The USGS gauging station (01491000) for the Greensboro watershed has monitored hydrology since 1948 and nutrient concentrations since 1965 (75.8049 W, 38.9737 N, 2.73 ft asl, Fig. 2.1). The Greensboro watershed is one of nine river input monitoring (RIM) watersheds in the Chesapeake Bay watershed. The total delivered nutrient export of the nine RIMs watersheds in the Chesapeake Bay represents nearly 80% of the nutrient contribution in the Bay watershed (Moyer 2016). As part of the Chesapeake Bay Program non-tidal monitoring network of 117 water quality monitoring stations, data from this network and the RIMs watersheds are used to measure progress toward meeting the Bay TMDL (USGS 2014). Nutrient data are collected and quantified to estimate export for the monitored tributaries and calibrate the Chesapeake Bay watershed Model. The nutrient data also provides insight into whether a relationship exists between measured concentrations, anthropogenic terrestrial management activities, and water quality (USGS 2014).

2.2.3 Best management practices data retrieval

CAST summarizes BMP implementation progress and nutrient loading scenarios at the land-river segment spatial scale, the smallest geographic scale within the Chesapeake Bay Model. Three land-river segments make up the Greensboro watershed (Fig. 2.1), and within each land-river segment, applied BMPs intercept nutrients (N, P, and TSS) within the following sectors: agriculture, rural-urban development, natural, septic systems, and animals. In the remaining paragraphs, terminology relevant to understanding BMP implementation and BMP effectiveness via CAST is italicized and defined in the Glossary at the end of this chapter.

I compiled the historical BMP implementation in the Greensboro watershed between 1985 and 2021 using CAST for this research. The various types of BMPs were classified into their respective sectors and then condensed into fewer groups for this research (Appendix A). The amount of BMP implementation for each *progress year* between 1985 and 2021 in each *land-river segment* within the Greensboro watershed is based on the *credited BMPs*, which include all functioning *annual BMPs* and *multi-annual BMPs* during their expected lifetimes. Annual BMPs are designed to have a short lifespan of less than one year and include many cultural BMPs, such as cover crops and conservation tillage practices, and are implemented yearly to receive the nutrient reduction benefit of annual BMPs. Functioning multi-annual BMPs include all structural BMPs (e.g., barnyard runoff controls, forest buffers, drainage controls, etc.) designed to reduce nutrients for more than one year.

2.2.4 Nutrient export scenarios

For this research, I focused on nutrient export originating from land-based nonpoint sources (Appendix B). The expected effect of credited BMPs is based on edge-of-stream nutrient export modeled by CAST and should fall below the annual land-based load allocation (LA) to meet the local TMDL LA prescribed for the CHOTF, which amounts to a 24%, 18%, and 7% reduction in N, P, and TSS, respectively. The nutrient export from point sources in the Greensboro watershed, including the Cedar Mobile Home Park WWTP (Residential/Municipal NPDES #MD0057847), Innovative Ideas, LLC industrial WWTP (NPDES # MDG499661), Shore sand and gravel industrial WWTP for the breeding pit (NPDES # MDG499784), Marydel Pit (NPDES # MD0070068), and Councell Plant (NPDES # MDG499787), should not exceed the waste load allocation (WLA) portion of the TMDL. The WLA is not a focus of this research.

I examined two types of nutrient loading scenarios in this research: (1) nutrient export with BMP implementation between 1985 and 2021 and (2) nutrient export without BMP implementation between 1985 and 2021. Each type of scenario is explained in the following paragraphs.

2.2.5 Land-based nutrient export scenarios without BMP implementation

I used CAST to project the LA nutrient export from the agriculture and development sectors to compare the 2021 progress year with BMP implementation and without BMP implementation. Equation 1 calculates the LA nutrient export based on the CAST 2010 No action edge-of-stream (EOS) nutrient loading rates for the agriculture (AL_{NA}) and development (DL_{NA}) sector and load source areas in 2021 before applying BMPs.

$$AL_{NA} \text{ or } DL_{NA}\ (\text{kg y}^{-1}) = Area_{NA}\ (\text{ha}) * LR_{NA}\ (\text{kg ha}^{-1}\ \text{y}^{-1}) \qquad \text{eq. 1}$$

where AL_{NA} is the predicted No-BMP nutrient export (kg y^{-1}) for all agricultural land in the progress year, DL_{NA} is the predicted No BMP nutrient export (kg y^{-1}) for all developed land in the progress year, $Area_{NA}$ (ha) is the progress year *Pre-BMP area* defined as the projected area of agricultural or development load sources designated as LA in the land-river segment before applying BMPs (Appendix B), and LR_{NA} (kg ha^{-1} y^{-1}) is the 2010 No-BMP areal EOS loading rates (Appendix C).

2.2.6 Land-based nutrient export scenarios with BMP implementation

I used CAST to project the LA nutrient export from the agriculture and development sectors to determine the overall BMP effect in 2010 and 2021. Equation 2 calculates the nutrient export calculation based on the loading rates modeled in the respective progress years and land-based load source areas after BMPs are credited.

$$AL_{BMP} \text{ or } DL_{BMP} \text{ (kg)} = Area_{BMP} \text{ (ha)} * LR_{BMP} \text{ (kg ha}^{-1} \text{ y}^{-1}) \qquad \text{eq. 2}$$

where AL_{BMP} is the nutrient export from land for all functioning agricultural BMPs in the progress year (kg y^{-1}), DL_{BMP} is the nutrient export from land for all functioning development BMPs in the progress year (kg y^{-1}), $Area_{BMP}$ (ha) is the progress year *post-BMP area* defined as the projected area of load sources designated as LA in the land-river segment after crediting all BMPs (Appendix B), and LR_{BMP} (kg ha^{-1} y^{-1}) is equal to the nutrient edge-of-stream (EOS) areal rates during the progress year (Appendix C). For this research, nutrient export is based on EOS, and overall results are compared to the CHOTF TMDL nutrient reduction goals.

2.2.7 Nutrient export uncertainty

CAST nutrient loading scenarios reflect the nutrient export after BMP implementation occurs in each sector, comprising various *load sources*, such as double-cropped land, grain with manure, and specialty crops, characterized by nutrient areal rate in kg^{-1} ha y^{-1} (Appendix D). This distinction is important because not all load sources receive an equal application of BMPs. For example, even though double-cropped land and specialty crops are sources of high nutrient export in the Greensboro watershed, cover crops were only applied to double-cropped agricultural land, not specialty crops. Another important distinction is that BMPs intercepting nutrient export may have differing types of benefits, which introduces uncertainty in modeled nutrient export (Table 2.2). The most common BMP benefit is *efficiency*. For example, the N efficiency of nutrient management plans applied to grain with manure is 10-15%. The same practices, however, will have a 3-5% N reduction if applied to grain without manure. Not all BMP implementation results in an efficiency benefit, however. Other BMPs could result in *load source conversion*. For example, land retirement converts cropland from a higher load source to a land use that lowers the overall nutrient export. In a few cases, a BMP could offer both benefits, such as forest and grass buffers. Lastly, a BMP such as a stream restoration project could reduce the overall nutrient export (load reduction) when nutrients are intercepted and no longer pass downstream. There is further uncertainty in modeled nutrient export because multiple BMPs are frequently applied to a single load source, which affects how CAST calculates the BMP interaction and projected nutrient export (Appendix E).

Table 2.2. **BMP classification and efficiency**. Abbreviation: "Benefit" is the benefit type where E is Efficiency (average %), LC is load source conversion which results in a change from high nutrient export to lower nutrient export, LCE is load source conversion with efficiency benefit, and LR is load reduction, "Sector BMP Classification" lists the BMP classes within a sector, N, P, and TSS list the efficiency range, "Life" indicates annual (A) or multi-annual (MA) BMP, "Units" indicates BMP measurement in area, length, or count. BMP efficiencies are based on Coastal Plain Uplands (Lowrance et al. 1997). Source: CAST Source data excel data sheet available at http://cast.chesapeakebay.net/.

Benefit	Sector: BMP classification	units	N	P	TSS	Life
Agriculture:						
E	Barnyard runoff control and Loafing lot	$km^2\ y^{-1}$	20	20	40	M.A.
E	Conservation plans	$km^2\ y^{-1}$	3-8	5-15	8-25	M.A.
E	Cover crop - commodity	$km^2\ y^{-1}$	5-15	0	0	A
E	Cover crop - traditional	$km^2\ y^{-1}$	4-45	0-15	0-20	A
E	Exclusionary fencing within buffers	$km^2\ y^{-1}$	21-31	45	60	M.A.
LCE	Forest buffer	$km^2\ y^{-1}$	31	45	60	M.A.
LCE	Grass buffers	$km^2\ y^{-1}$	21	45	60	M.A.
E	Manure incorporation or injection	$km^2\ y^{-1}$	8-12	14-22	0	A
E	Nutrient management practices	$km^2\ y^{-1}$	3-15	1-20	0	A
E	Off-stream watering without fencing	$km^2\ y^{-1}$	5	8	10	M.A.
E	Precision grazing and horse pasture	$km^2\ y^{-1}$	9	24	30	A
E	Tillage: low, conservation, high	$km^2\ y^{-1}$	2-12	7-26	18-79	A
LC	Tree planting	$km^2\ y^{-1}$				M.A.
E	Water control structure	$km^2\ y^{-1}$	33	0	0	M.A.
LCE	Wetland creation	$km^2\ y^{-1}$	16-30	32-33	9-27	M.A.
LCE	Wetland restoration	$km^2\ y^{-1}$	16-42	22-40	9-31	M.A.
LC	Land retirement and alternative crop	$km^2\ y^{-1}$				M.A.
Animal:						
E	Animal waste management	AU	0	0	0	M.A.
E	Broiler and poultry litter amendments	AU	50	0	0	A
E	Manure transport	metric tons	0	0	0	A
E	Mortality composter	AU	0	0	0	M.A.
E	Riparian fencing	AU	100	100	0	M.A.
Development:						
E	Erosion and sediment control	$ha\ y^{-1}$	0	0	74-90	A
LCE	Infiltration and filtering practices	$ha\ y^{-1}$	10-85	10-85	50-95	M.A.
E	Rural-urban nutrient management plan	$ha\ y^{-1}$	4-20	0-10	0	A
E	Stormwater practices	$ha\ y^{-1}$	treated water volume calculation			M.A.
E	Street sweeping	$ha\ y^{-1}$	0-4	1-10	2-21	A
LCE	Forest buffer	$ha\ y^{-1}$	25	50	50	M.A.
LC	Tree planting	$ha\ y^{-1}$				M.A.
E	Wetlands, wet/dry ponds, dry detention ponds	$ha\ y^{-1}$	20	45	60	M.A.
Natural						
E	Forest harvesting applied to deforestation	$ha\ y^{-1}$	50	60	60	M.A.
LR	Non-Urban stream restoration	$meter\ y^{-1}$	0.075	0.068	248	MA
Septic systems:						
LC	Connection to public sewer	$system\ y^{-1}$	100	0	0	M.A.
E	Conventional denitrification system	$system\ y^{-1}$	50-75	0	0	M.A.
E	Septic effluent via in-situ soil treatment	$system\ y^{-1}$	38-50	0	0	M.A.
E	Septic pumping	$system\ y^{-1}$	5	0	0	A

2.2.8 Data limitations

Since multiple agencies in the Bay watershed contribute to the BMP implementation data record, underestimating and overestimating BMP implementation and human errors are possible. A description of data limitations and explanations are presented in Table 2.3 but does not preclude using the CAST data for assessment purposes. Examples of data limitations that can underestimate BMPs include **voluntary BMP implementation**, efforts to **protect individual producer privacy** rights (Hively et al. 2018), and the **absence of reporting** by jurisdictions. On the other hand, **expired BMPs**, a human error such as using inconsistent **BMP definitions,** and **BMPs funded by multiple agencies** can overestimate BMPs. The effect of management scenarios for a given year at a defined geographic scale, including county-level and various watershed scales, also contributes to nutrient export errors.

Table 2.3. Summarized explanations of overestimated and underestimated BMPs.

Data limitation	Explanation
Underestimating BMPs	
Voluntary BMP implementation	Private property owners can pay out of pocket to implement BMPs and are under no obligation to report their efforts to government agencies for inclusion in the Chesapeake Bay Model.
Protect individual producer privacy rights	BMPs reported by CAST are withheld at finer spatial scales if less than five units of a BMP exist at a spatial scale smaller than the county; instead, these few units of a BMP will appear at the county scale.
Absence of BMP reporting by jurisdictions	There are insufficient resources to compile and report the data or historical records of BMP implementation in the jurisdiction that do not exist.
Overestimating BMPs	
Expired multi-annual BMPs	BMPs with a lifetime of 10 to 15 years may remain in management scenarios even after the BMPs are no longer functioning.
Inconsistent BMP definitions	An example is reporting traditional cover crops (unfertilized) instead of commodity cover crops (fertilized) which affect modeled N loading rates differently.
BMPs funded by multiple agencies	Both funding agencies hold BMP implementation records and result in reporting of the entire BMP area by each agency instead of the portion funded.

2.2.9 Statistical analysis

I used SigmaPlot v 15 to conduct mean group comparisons and create linear regression plots. Linear regression models depicted time trends of BMP implementation (units: septic tanks, length, area, or animal units). Using linear regression, I also described nutrient (N, P, and SS) export trends versus progress years based on two scenarios: No BMP implementation and BMP implementation. The findings can be further verified by testing the trends using statistical tests accounting for autocorrelation in the time series.

To determine if the TMDL may have influenced BMP implementation levels, I compared means of the BMP implementation pre-TMDL (defined as implementation reported between 1985 and 2010, unless otherwise stated) or post-TMDL, which occurred between 2011 and 2021, unless otherwise stated. I conducted parametric t-tests to compare the BMP implementation group means. Welch's t-test result was chosen if the Brown-Forsythe equal variance test failed. I selected the Student's t-test result if the equal variance test passed. Next, I applied the Holm-Sidak method to adjust the pairwise test results for multiple comparisons. The findings can be further verified by testing autocorrelated data.

To test a difference in the nutrient export linear regression model and slope between No BMP implementation and BMP implementation scenarios, I conducted a one-way ANCOVA (analysis of covariance) using the Holm-Sidak method for pairwise comparisons of factors. The results of statistical tests were categorized as significant (S, $p < 0.05$), marginally significant (MS, $0.05 \leq p < 0.10$), or not significant (NS, $p \geq 0.10$).).

2.3 Results: Historical BMP implementation

Since the mid-1980s, implementing BMPs has been crucial in the Chesapeake Bay clean-up effort. In the following sections, I summarize the historical BMP implementation levels in the Greensboro watershed. Table 2.4 summarizes significant t-tests and trends for BMPs implemented in the natural, septic systems, and rural-urban development sectors.

Table 2.4. Summary of Natural, Septic systems, and Rural-urban development trendlines and t-tests of mean amount of BMP implementation between post-TMDL and pre-TMDL. Post-TMDL is 2011 – 2021 unless otherwise stated, and pre-TMDL is between 1985 -2010 unless otherwise stated. The **T-test** of whether post-TMDL is greater than pre-TMDL reports the following results: Y indicates post-TMDL mean is greater than pre-TMDL mean, N indicates post-TMDL is less than pre-TMDL, NS is no significant difference, alternative pre- or post-TMDL timeframe is stated if applicable, and p reports values unless designated as *** (< 0.0001) or ** (<0.001). The trend line displayed on the figure panels is summarized by time period, p-value, slope, and units are reported.

Fig	**Sector: BMP classification**	**T-tests: Post-TMDL > Pre-TMDL**	**Result**	**p**	**Trend: Time**	**p**	**slope**	**unit**
	Sector: Natural							
2a	Non-Urban stream restoration	n/a	Increased post-TMDL	n/a				
2b	Forest harvesting	Y		0.05				
	Sector: Septic systems							
3a	Connection to public sewer	Y		**				
3b	Conventional denitrification system	Y		**	1986-2010	***	0.13	system y^{-1}
3b	Conventional denitrification system				2011-2021	***	7	system y^{-1}
3c	Septic pumping	Y		**				
	Sector: Rural-urban development							
3d	Rural-urban nutrient management plan	Y		**				
3e	Tree planting and forest buffer	Y	2015-2021 > Pre-TMDL	**	2015-2021	0.003	0.03	ha y^{-1}
3f	Erosion and sediment control and street sweeping	N	Post-TMDL < Pre-TMDL	0.06				
3g	Wetlands, wet/dry ponds, dry detention ponds	Y	2010-2021 > Pre-TMDL	**	1986-2009	***	2.4	ha y^{-1}
3h	Infiltration and filtering practices	Y	2009-2021 > Pre-TMDL	**	1991-2008	***	1.4	ha y^{-1}
3i	Stormwater practices	N	Post-TMDL < Pre-TMDL	**	1987-1996	0.0001	21	ha y^{-1}
3i	Stormwater practices				2011-2021	0.0001	-14	ha y^{-1}

Additional BMP descriptions are provided in the Glossary at the end of this chapter, and the CAST model documentation details for BMPs are found in (Pickford 2022; CBP 2023).

2.3.1 Natural best management practices (BMPs)

After the TMDL, more BMP implementation on natural land cover types such as naturally forested areas, non-tidal floodplain wetlands, headwater or isolated wetlands, and waterways (CBP 2020d) occurred in the Greensboro watershed. For example, there were no reported stream restorations before the TMDL, but after the TMDL, the length of non-urban streams restored increased by a small amount, and from 2014 to 2015, the length of restored streams more than doubled (Fig. 2.2a). The mean area under forest harvesting BMPs, shown in Figure 2.2b, significantly increased by 24% after 2011 ($p < 0.05$, Table 2.4, Table F1). These BMPs are designed to reduce sediments and nutrients from logging activities, including road building, site preparation, and log removal. In 2021, there were 0.36 ha of wetland **rehabilitation** in the Caroline County portion of the watershed. These data show the increased implementation of natural BMPs within the Greensboro watershed after the TMDL.

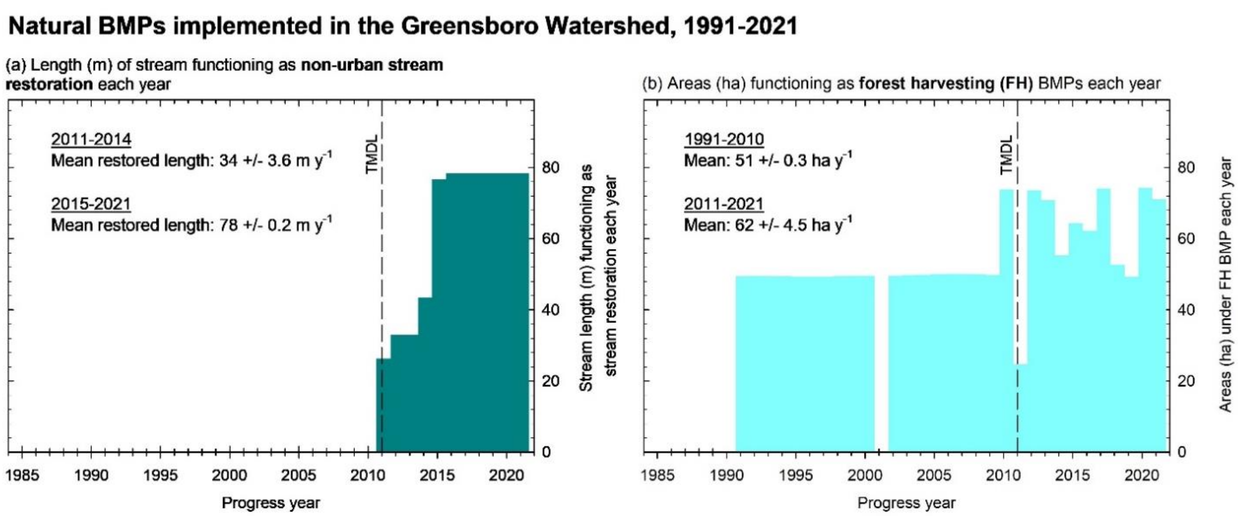


Figure 2.2. Natural BMPs affect more land areas in the Greensboro watershed after 2011.

2.3.2 Septic system best management practices (BMPs)

Septic system BMPs greatly increased after the TMDL (Table 2.4), primarily due to reported efforts in the Kent County portion of the Greensboro watershed. Figure 2.3a illustrates that septic tank connections to public sewer systems leveled out after 2013 ($r^2 = 0.83$, $p < 0.001$), averaging 178 ± 0.73 connected systems each year. There was also a significant increase in the number of conventional denitrification systems (Fig. 2.3b) and pumped septic tanks (Fig. 2.3c) after 2011, representing a large increase over prior rates ($p < 0.001$, Table F2). Septic pumping is recommended once every three to five years, which removes solids from the tank to prevent clogging and overall failure of the septic system. In Kent County, DE, more than 100 septic systems in 2021 designed to reduce TN by 38% (enhanced) or 50% (advanced) employed an in-situ soil treatment system with no secondary treatment or enhanced denitrification technology. These data show that septic system BMPs significantly increased post-TMDL, notably the number of annual septic tanks pumped and multi-annual connected systems to public sewer systems, denitrification systems, and recent instances of in-situ soil treatment per non-denitrification system that were only reported in the Kent County, DE portion of the watershed.

2.3.3 Rural-urban development best management practices (BMPs)

Figure 2.3 (panels d-i) depicts the annual amount of functioning rural-urban development BMPs in areas of dense, impervious surfaces and structures such as construction areas, turf grass, and roadways (CBP 2020d). An example is a yearly nutrient management plan (NMP), which outlines how to manage N and P applied to turf and landscape plants for commercial applicators. Figure 2.3d shows the area covered by annual rural-urban NMPs

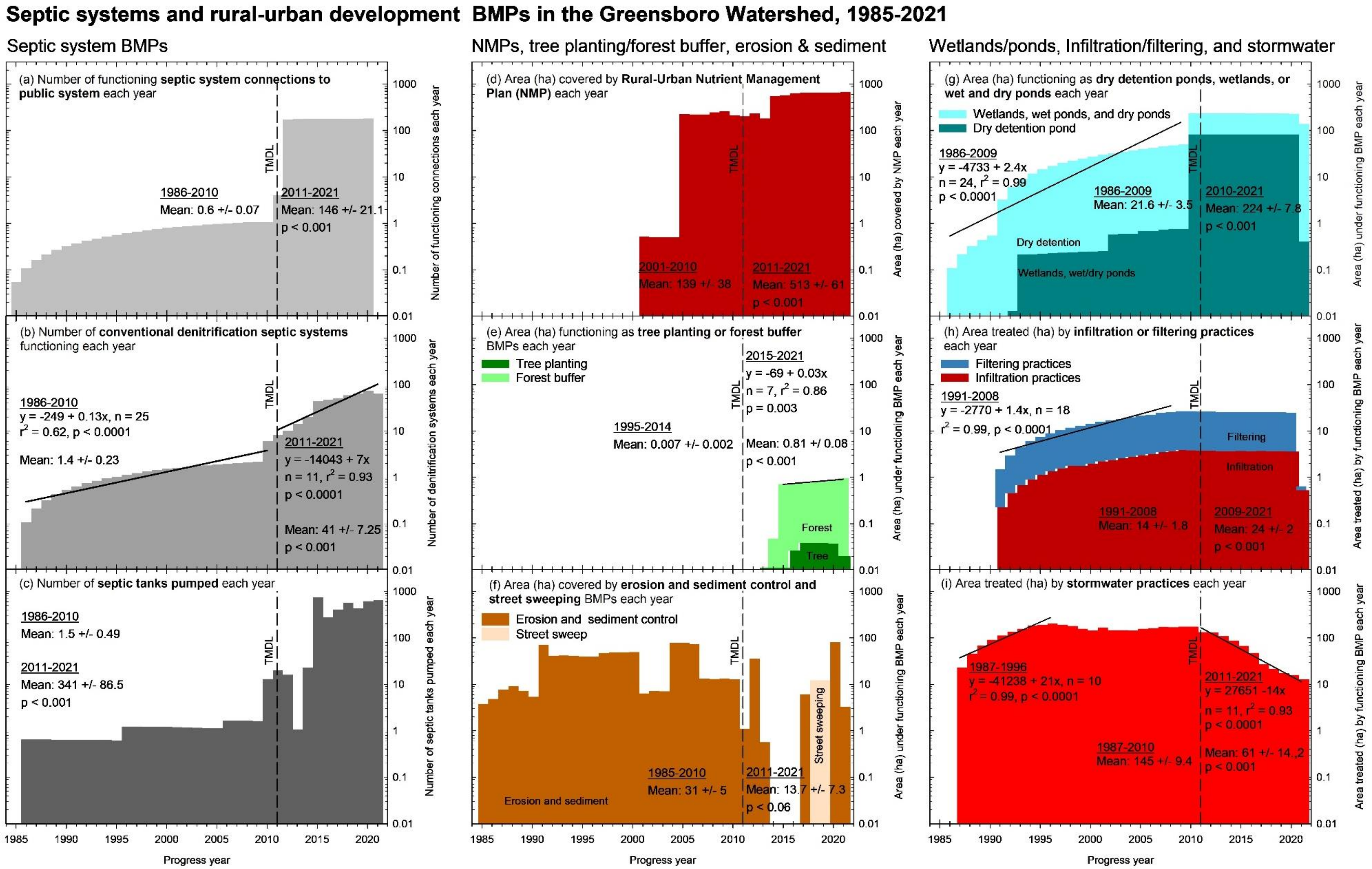


Figure 2.3. BMPs applied to septic systems in the Greensboro watershed increased after the TMDL. Rural-urban development BMPs also increased in the watershed except for sediment and erosion control and stormwater practices.

increased significantly after the TMDL, and the average area increased by 270% ($p < 0.001$, Table F2). Newly implemented development BMPs such as multi-annual tree planting and forest buffer (Fig. 2.3e) and annual street sweeping (Fig. 2.3f) occurred shortly after the TMDL approval. Multi-annual development BMPs such as wetlands and wet and dry ponds designed to intercept stormwater (Fig. 2.3g) and infiltration depressions that trap sediment and allow for water infiltration or vegetated strips designed to filter nutrients and particles from overland flow (Fig. 2.3h) also increased post-TMDL ($p < 0.001$). In contrast, the mean area treated by stormwater management practices for new and redevelopment projects decreased significantly post-TMDL ($p < 0.001$, Fig. 2.3i). Post-development, implemented stormwater practices such as bioretentions, rain gardens, and bioswales achieve at least a 25% annual overland flow volume reduction. A comparison of pre- and post-TMDL mean areas functioning as erosion and sediment control practices (Fig. 2.3f) revealed the post-TMDL marginally decreased relative to pre-TMDL ($p = 0.06$, Table 2.4). The data show that stormwater practices and erosion and sediment control practices decreased after the TMDL; however, nutrient management plans, wetlands, wet ponds, dry ponds, and infiltration and filtering practices significantly increased after the TMDL in the watershed.

2.3.4 Agricultural best management practices (BMPs)

Most BMPs implemented in the Greensboro watershed aim to reduce nutrients exported from agriculture. T-tests indicated that many BMPs increased significantly after the TMDL and some of the significant trends show that BMPs increased annually before the TMDL (Table 2.5). Detailed T-tests are provided in Tables F4 and F5. These agricultural BMPs are depicted in Figures 2.4 and 2.5 and discussed in the following section.

Table 2.5. Summary of Agriculture sector trendlines and t-tests of mean amount of BMP implementation between post-TMDL and pre-TMDL. Post-TMDL is 2011 – 2021 unless otherwise stated, and pre-TMDL is between 1985 - 2010 unless otherwise stated. The **T-test** of whether post-TMDL is greater than pre-TMDL reports the following results: Y indicates post-TMDL mean is greater than pre-TMDL mean, N indicates post-TMDL is less than pre-TMDL, NS is no significant difference, alternative pre- or post-TMDL timeframe is stated if applicable, and p reports values unless designated as *** (< 0.0001) or ** (<0.001). The trend line displayed on the figure panels is summarized by time period, p-value, slope, and the unit is $km^2 y^{-1}$.

		T-tests: Post-TMDL > Pre-TMDL			**Trend**		
Fig	**Sector: Agriculture BMP classification**		**Results**	**p**	**Time**	**p**	**Slope $km^2 y^{-1}$**
4a	Off-stream watering without fencing	Y		**	1994-2010	***	0.006
4b	Barnyard runoff control and Loafing lot management	Y		**	1993-2008	***	0.0002
4b	Barnyard runoff control and Loafing lot management				2009-2013	0.04	0.005
4b	Barnyard runoff control and Loafing lot management				2014-2021	0.002	0.005
4c	Management practices for pasture and grazing and horse pasture	Y		0.002			
4d	Cover crop and commodity planting	Y		**	1999-2010	0.008	0.64
4e	Manure incorporation or injection	n/a	Increased post-TMDL	n/a			
4f	Water control structure	Y		**	1985-2015	***	0.02
4g	High-till	Y	2014-2021 > Pre-TMDL	**	1989-2013	***	0.5
4g	High-till				2014-2021	0.01	-2.2
4h	Conservation tillage	Y	2014-2021 > Pre-TMDL	**	1989-2013	***	0.3
4h	Conservation tillage				2014-2021	0.006	-2.19
4i	Low-till	Y	2018-2021 > Pre-TMDL	**			
5a	Nutrient management practices	Y	2012-2021 > Pre-TMDL	**	1999-2011	***	2.4
5a	Nutrient management practices				2012-2021	***	12.5
5b	Conservation plans	Y		**	1985-2005	0.007	0.6
5b	Conservation plans				2006-2010	***	13
5b	Conservation plans				2016-2021	0.006	-13
5c	Land retirement and alternative crop	Y		**			
5d	Wetland creation	NS		0.236	2001-2009	***	0.003
5d	Wetland creation				2015-2021	0.002	-0.002
5e	Wetland restoration	Y		**	1997-2006	0.0002	0.7
5e	Wetland restoration				2007-2011	0.02	1.3
5e	Wetland restoration				2012-2021	***	0.12
5f	Tree planting	Y		**	1985-2010	***	0.36
5f	Tree planting				2011-2021	***	0.04
5g	Forest buffer	NS		0.298	2013-2021	0.002	0.15
5h	Grass buffers	Y		**			
5i	Exclusionary fencing within buffers	N	Post-TMDL < Pre-TMDL	0.008	2015-2021	0.02	-0.01

Agricultural BMPs for croplands, pastures, and barnyards

Agriculture BMPs aimed at reducing the impact of livestock on stream corridors (Fig. 2.4a), barnyard runoff, and loafing lots, which include areas frequently and intensively used by people, animals, or vehicles (Fig. 2.4b), and grazing and pastures (Fig. 2.4c) increased significantly after the TMDL. For example, the areas devoted to the installation of multi-annual, alternative drinking water sources for animals away from streams significantly increased to a mean of 0.49 ± 0.4 km^2, 15 times greater than pre-TMDL, and BMPs installed to minimize barnyard runoff and loafing lots significantly increased to a mean of 0.13 ± 0.01 km^2, 22 times greater than pre-TMDL ($p < 0.001$, Table 2.5). Annual precision intensive rotational and prescribed grazing practices reduce the impact of high animal concentrations and ensure at least a 60% vegetative cover in pastures. These practices increased significantly between 2011 and 2021 compared to 2009 – 2010 by a factor of 10 ($p = 0.002$, Table F3).

Cropland BMPs such as annual cover crops (Fig. 2.4d), manure incorporation or injection (Fig. 2.4e), tillage practices (Fig. 2.4, panels g-i), and multi-annual water control structures (Fig. 2.4f) also increased significantly post-TMDL. For example, the mean areas of croplands with drainage ditches affected by water control structures increased by 30, and traditional cover crops (unfertilized, no spring harvest) increased 7.25 times ($p < 0.001$). Commodity cover crops (fertilized, harvested in the spring) increased by 4 ($p = 0.004$). Similarly, annual tillage practices that achieve at least 60% (high residue, Fig. 2.4g), 30 -59% (conservation, Fig. 2.4h), or 15-29% (low residue, Fig. 2.4i) crop residue cover on the soil surface immediately after planting increased significantly ($p < 0.001$, Table 2.5). However, after 2018, high tillage and conservation tillage practices significantly decreased as low residue (no-tillage) increased ($p \leq 0.05$). Low residue (no-tillage) leaves 15 – 29% of crop residue, less than 40% soil disturbance. Additionally, newly implemented practices where manure was injected into the soil immediately

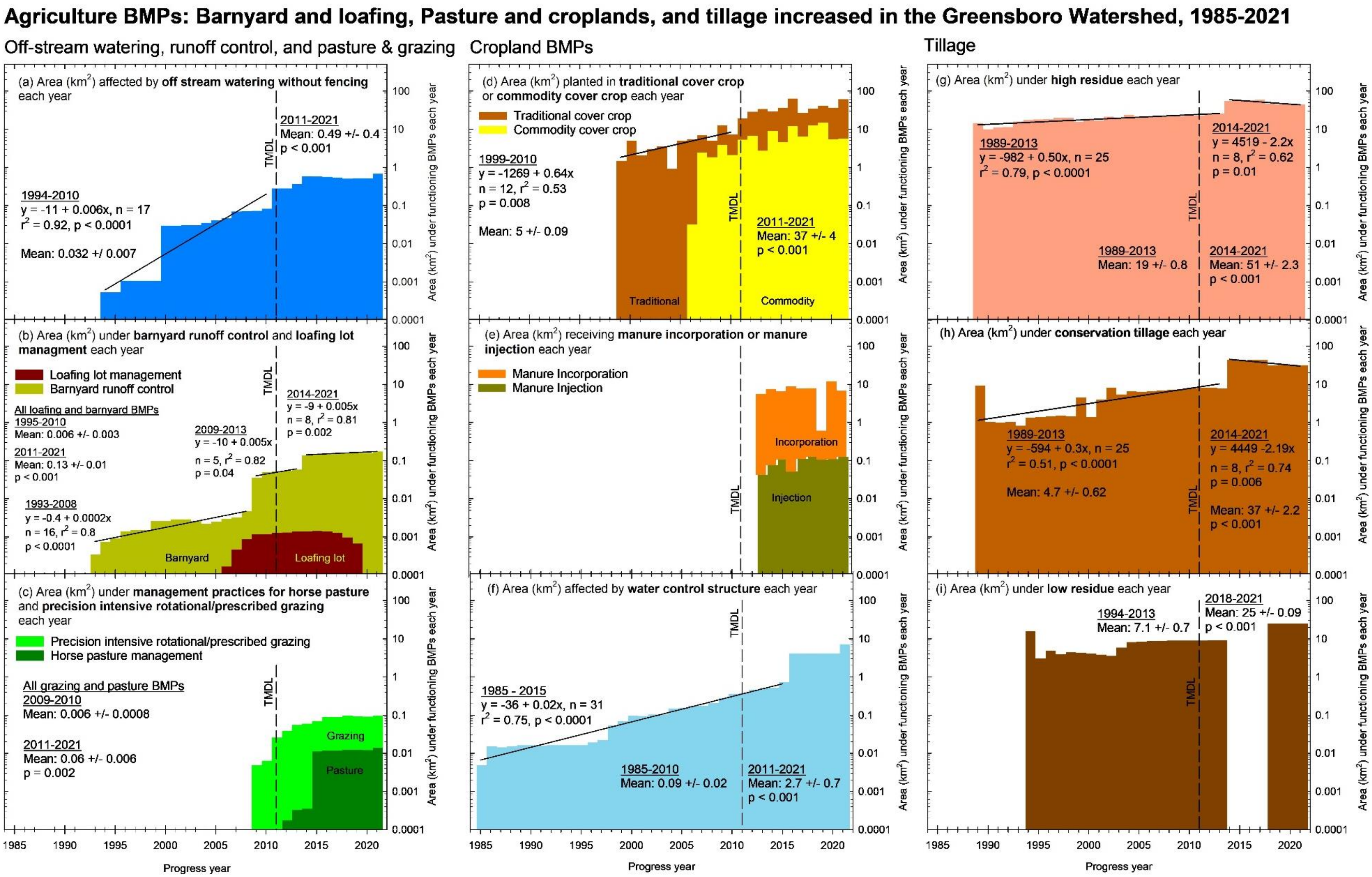


Figure 2.4. Overall, agricultural BMPs applied to pastures, stream corridors, barnyards, and croplands increased after the TMDL approval in December of 2010.

or incorporated over 1-3 days occurred shortly after the TMDL. The data show significantly more BMPs applied to barnyards, stream corridors, and croplands post-TMDL.

Cropland nutrient management and agricultural non-cropland BMPs

Nutrient management BMPs applied to croplands and many of the agricultural non-cropland BMPs, but not all, significantly increased post-TMDL (Table 2.5). For example, after the TMDL annual nutrient management plans (Fig. 2.5a), 10-year agricultural soil conservation and water quality plans (Fig. 2.5b), and retired marginal croplands and cropland areas planted in alternative crops such as unfertilized, permanent warm-season grasses (Fig. 2.5c) covered 8.6, 3.9, and 3.7 times more area, respectively ($p < 0.001$, Table F4). Annual nutrient management plans continued to increase post-TMDL and at a yearly rate more than five times greater than pre-TMDL. Annual nutrient management plans prescribe the placement, rate, and timing of N and P BMPs applied to croplands. In contrast, agricultural soil conservation and water quality plans identify agronomic, management, and engineering practices to maintain natural resources and protect and improve farmland's soil productivity and water quality on farmlands. The agricultural areas converted to new wetlands (Fig. 2.5d) pre- and post-TMDL were not significantly different; however, the average area of degraded wetlands restored to their natural function (Fig. 2.5e) after the TMDL increased 4.5 times ($p < 0.001$). Significantly increasing rates of wetland restoration efforts were evident pre-TMDL and continued to increase post-TMDL but at a slower rate. The first instance of overall improvements in wetland functions impacting 0.36 ha occurred in 2021 in the Caroline County portion of the watershed. After the TMDL, tree planting (Fig. 2.5f) on highly erodible agricultural land outside of the riparian zone and grass buffers (Fig. 2.5h) designed to filter nutrients and

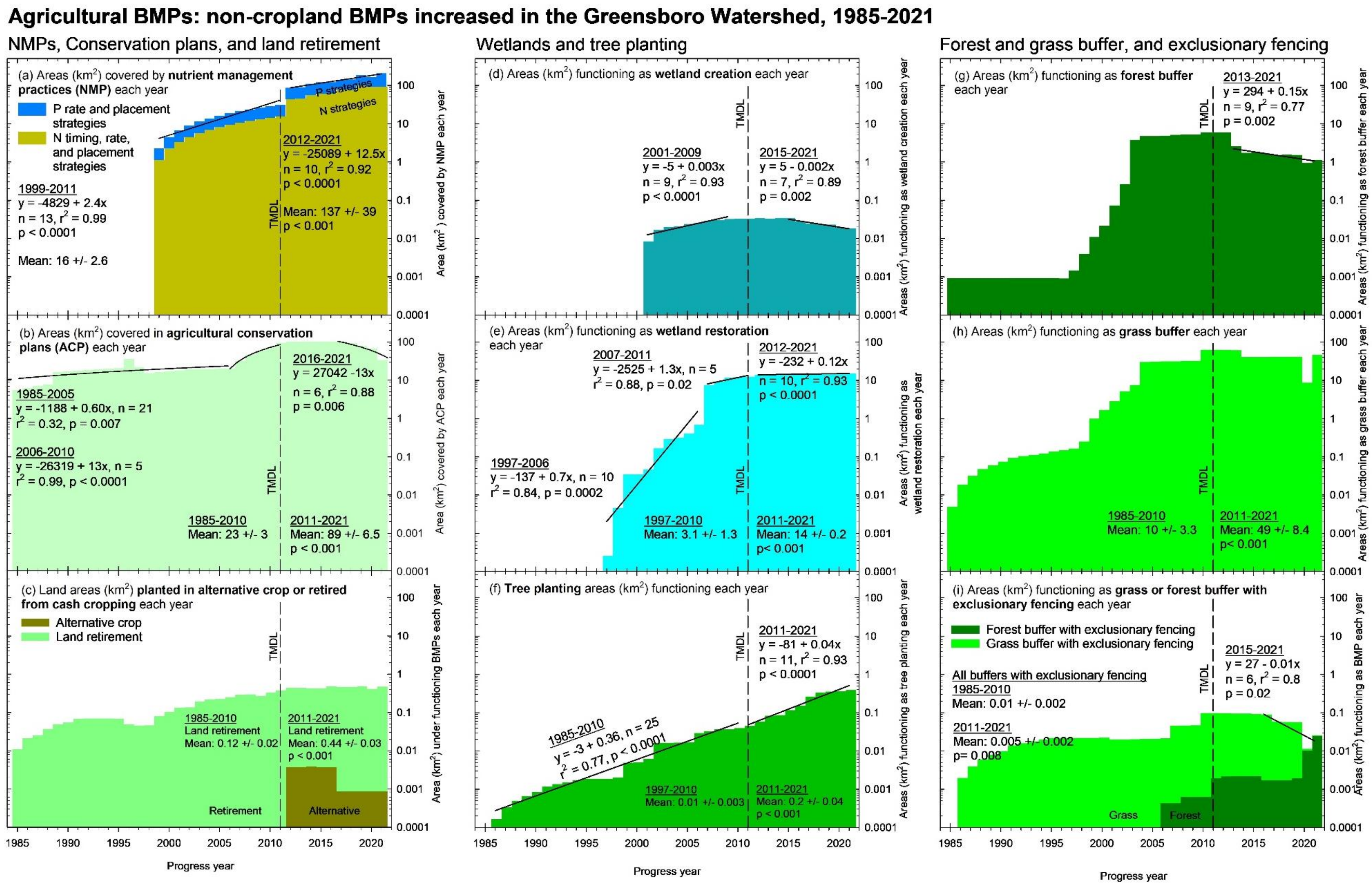


Figure 2.5. Except for wetland creation, forest buffers, and exclusionary fencing in grass and forest buffers, agricultural non-cropland BMPs and nutrient management BMPs applied to croplands significantly increased after the TMDL.

sediment from overland flow significantly increased ($p < 0.0001$). The rate of installing tree planting areas continued to increase post-TMDL but at a slower rate. Grass buffers increased by nearly 400% as forest buffers (Fig. 2.5g) significantly decreased post-TMDL. Additionally, grass and forest buffers with exclusionary fencing decreased significantly (Fig. 2.5i). With a few exceptions, the data show that many non-cropland BMPs increased post-TMDL.

2.3.5 Animal and manure management practices

The importance of implementing animal BMPs cannot be understated since the poultry industry has continued to grow its operations on the Delmarva Peninsula. These BMP actions remain critical in achieving the TMDL water quality goals. However, not all animal BMPs increased after the TMDL. T-tests indicated greater post-TMDL mean values for riparian fencing, mortality composters, and animal waste management. Trends also showed these BMPs were increasing pre-TMDL (Table 2.6). In contrast, poultry manure transport and litter amendments decreased post-TMDL (Table F5). These animal BMPs are depicted in Figure 2.6 and discussed in the following paragraph.

Animal BMPs do not eliminate nutrients but transport nutrients from one place to another. For instance, BMPs such as animal waste management and manure transport temporarily store manure until the manure is applied onto croplands. In the Greensboro watershed, there were significant increases in the number of animal units (e.g., 1 A.U. = 125 adult chickens or a 454 kg cow) affected by riparian fencing (Fig. 2.6a), mortality composting (Fig. 2.6b), and animal waste management (Fig. 2.6d) post- TMDL ($p < 0.001$, Table 2.6). For example, Figure 2.6a depicts the implementation of riparian fencing, which significantly increased by 1.1 AU y^{-1} between 1986 and 1994 ($p < 0.0001$). Post-TMDL, riparian fencing

Table 2.6. Summary of Animal sector trendlines and t-tests of mean amount of BMP implementation between post-TMDL and pre-TMDL. Post-TMDL is 2011 – 2021 unless otherwise stated, and pre-TMDL is a time between 1985 -2010 unless otherwise stated. The **T-test** of whether post-TMDL is greater than pre-TMDL reports the following results: Y indicates post-TMDL mean is greater than pre-TMDL mean, N indicates post-TMDL is less than pre-TMDL, NS is no significant difference, alternative pre- or post-TMDL timeframe is stated if applicable, and p reports values unless designated as *** (< 0.0001) or ** (<0.001). The trend line displayed on the figure panels is summarized by time period, p-value, slope, and the unit is A.U. y^{-1}.

		T-tests: Post-TMDL > Pre-TMDL		**Trend**		
Fig	**Sector: Animal BMP classification**	**Results**	**p**	**Time**	**p**	**Slope A.U. y^{-1}**
6a	Riparian fencing	Y 2010-2021 > Pre-TMDL	**	1986-1994	***	1.1
6b	Mortality composter	Y 2010-2021 > Pre-TMDL	**	1988-2009	***	61
6b	Mortality composter		**	2010-2021	***	239
6c	Broiler and poultry litter amendments	N 2012-2021 < Pre-TMDL	**	2012-2021	0.0007	-318
6d	Animal waste management	Y 2012-2021 > Pre-TMDL	**	1985-2010	***	2,386
6d	Animal waste management			2011-2021	***	4,766
6e	Poultry manure transport from a Greensboro watershed County to a place outside of the tri-county region	N Post-TMDL < Pre-TMDL	0.067			
6f	Poultry and dairy manure transport from a Greensboro watershed County to another Greensboro watershed County	NS	0.64			

prevented an average of 49 ± 5 A.U. each year from grazing in riparian areas (Table F5, Table 2.6). Increased use of mortality composter and animal waste management after the TMDL was largely due to reported uses in the Kent County, DE portion of the Greensboro watershed. In contrast, reported uses of broiler and poultry litter amendments, which reduce ammonia volatilization and minimize ammonia emissions from poultry houses (Fig. 2.6c), significantly decreased by 318 AU y^{-1} post-TMDL ($p < 0.001$, Table 2.6). Efforts to transport poultry manure from a county within the Greensboro watershed (Caroline, Queen Anne, and Kent counties) to other counties decreased post-TMDL (Fig. 2.6e, Table F5). There was no significant difference between mean groups, pre-and post-TMDL, representing the mean metric ton of poultry and dairy manure transport from a county within the Greensboro watershed to another county also

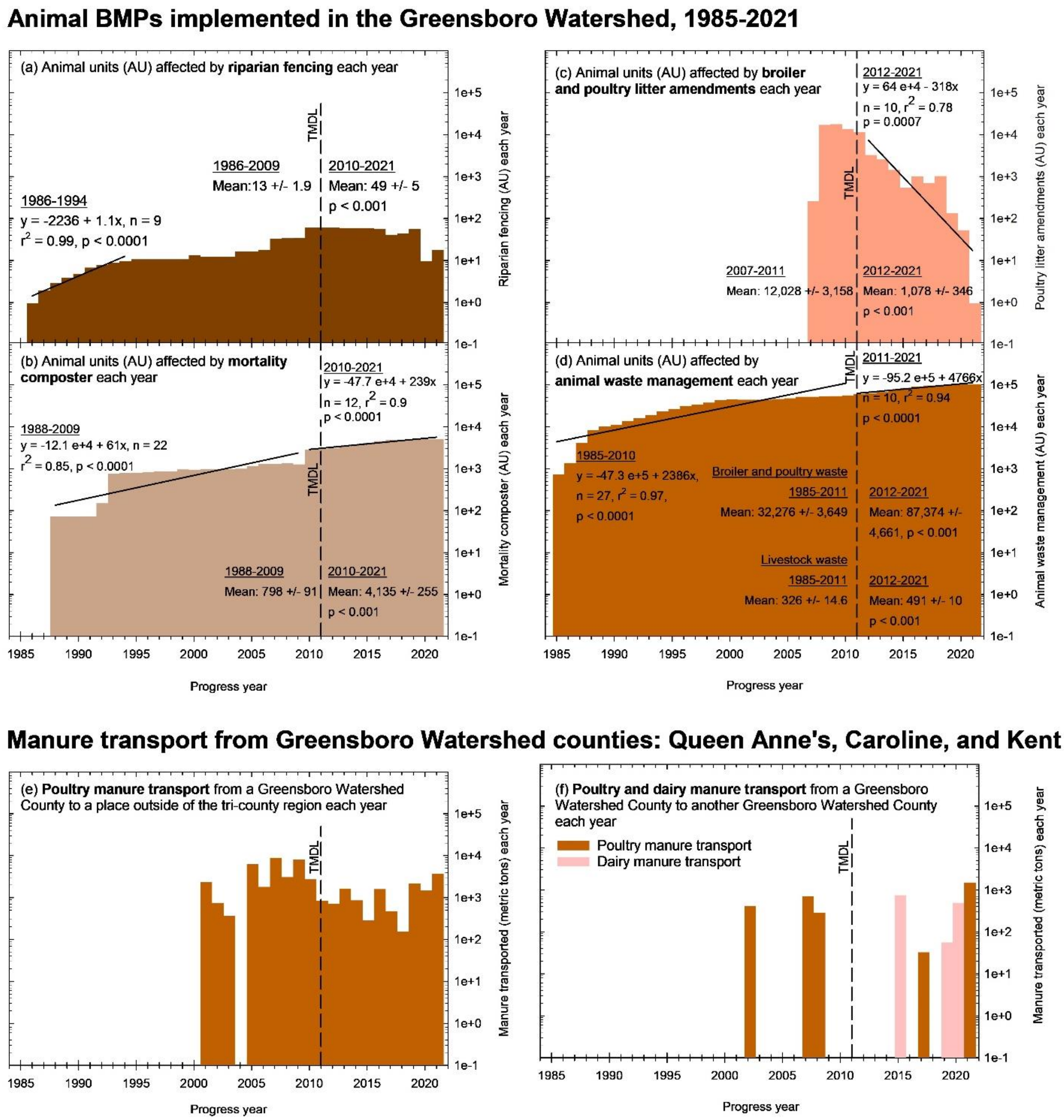


Figure 2.6. Apart from manure transport and poultry litter amendments, animal BMPs increased over progress years in the Greensboro watershed.

within the Greensboro watershed (Fig. 2.6f). These data show significant increases in using riparian fencing, mortality composting, and animal waste management BMPs. Post-TMDL, manure structures needed to collect, transfer, and store broiler and poultry waste averaged 87,374 ± 4,661 animal units each year, an increase of 2.7 times above pre-TMDL uses. The data also revealed significantly fewer instances of applied poultry litter amendments and manure transport post-TMDL.

2.3.6 County-scale and watershed summary of BMP implementation

Overall, the effect of the TMDL led to higher amounts of BMP implementation in the natural and rural-urban development sectors, and the rate of implementing septic denitrification systems post-TMDL was 54 times greater than pre-TMDL levels (Figs 2.3a-c, Table 2.4). Only two instances of rural-urban development BMP implementation, erosion and sediment control (Fig. 2.3f) and stormwater practices (Fig. 2.3i), decreased after the TMDL. Many agricultural and animal BMPs also increased after the TMDL (Tables 2.5 and 2.6), and manure incorporation and manure injection were newly implemented practices after the TMDL (Fig. 2.4e). However, the data revealed significant reductions in implementing high-till, conservation till, and conservation plans in recent years (Figs. 2.4g, 2.4h, 2.5b). Significant trend lines also showed notable change rates. For example, nutrient management practices increased 5.2 times after the TMDL (Fig. 2.5a, Table 2.5), and animal waste management nearly doubled after the TMDL (Fig. 2.6d), from 2,386 AU y^{-1} to 4,766 AU y^{-1}; however, no significant differences in manure transport (Figs. 2.6, panels e-f) indicated that more animal waste remained in the tri-county region. The data indicate much higher BMP implementation after the TMDL across various load sources in all sectors. However, animal BMPs have become responsible for safely storing increasing amounts of animal waste. Unfortunately, the animal waste management BMP does not reduce nutrients but attempts to move it elsewhere. In the case of the Greensboro watershed, since no significant changes have occurred with manure transport, it is reasonable to assume that much more manure remained within the tri-county region and was likely applied to croplands.

2.4 Results: Nutrient export due to BMP implementation

For this research, I describe estimates of BMP effectiveness based on the edge-of-stream nutrient export from land-based load allocation load sources in the agriculture and development sectors. First, I present the total edge-of-stream nutrient export trend results for the agriculture and development sectors under the No-BMP and BMP action scenarios, followed by the nutrient export from all sectors in progress year 2021 after BMP implementation. Lastly, I compare the nutrient export affected by BMP implementation in progress year 2021, following ten years of BMP implementation, to nutrient export in progress year 2010 when pre-TMDL BMP implementation levels affected nutrient export.

2.4.1 Ege-of-stream nutrient export: Agriculture and Development

The data shown in Figure 2.7 indicates **agriculture land-based BMPs** resulted in significant N (Fig. 2.7a), P (Fig. 2.7b), and TSS (Fig. 2.7c) edge-of-stream nutrient reductions between 1985 to 2021 ($p < 0.0001$). ANCOVA tests indicated that the P and TSS fluxes decreased 18 and 10 times faster with BMPs than without BMPs ($p < 0.001$). In contrast, the overall nutrient export from the **rural-urban development sector** increased significantly between 1985 – 2021 (Fig. 2.7, panels d-f). ANCOVA tests indicate that development land-based BMP implementation slightly lowered the overall mean edge-of-stream **N export means** (Fig. 2.7d, $p = 0.003$) and TSS (Fig. 2.7f, $p < 0.001$) when compared to the No-BMP action scenarios. An ANCOVA equal slopes test of the edge-of-stream N export between the No-BMP action and BMP action scenarios shown in Figure 2.7d detected no significant differences in slope (453 kg/y y^{-1}, Table 2.7).

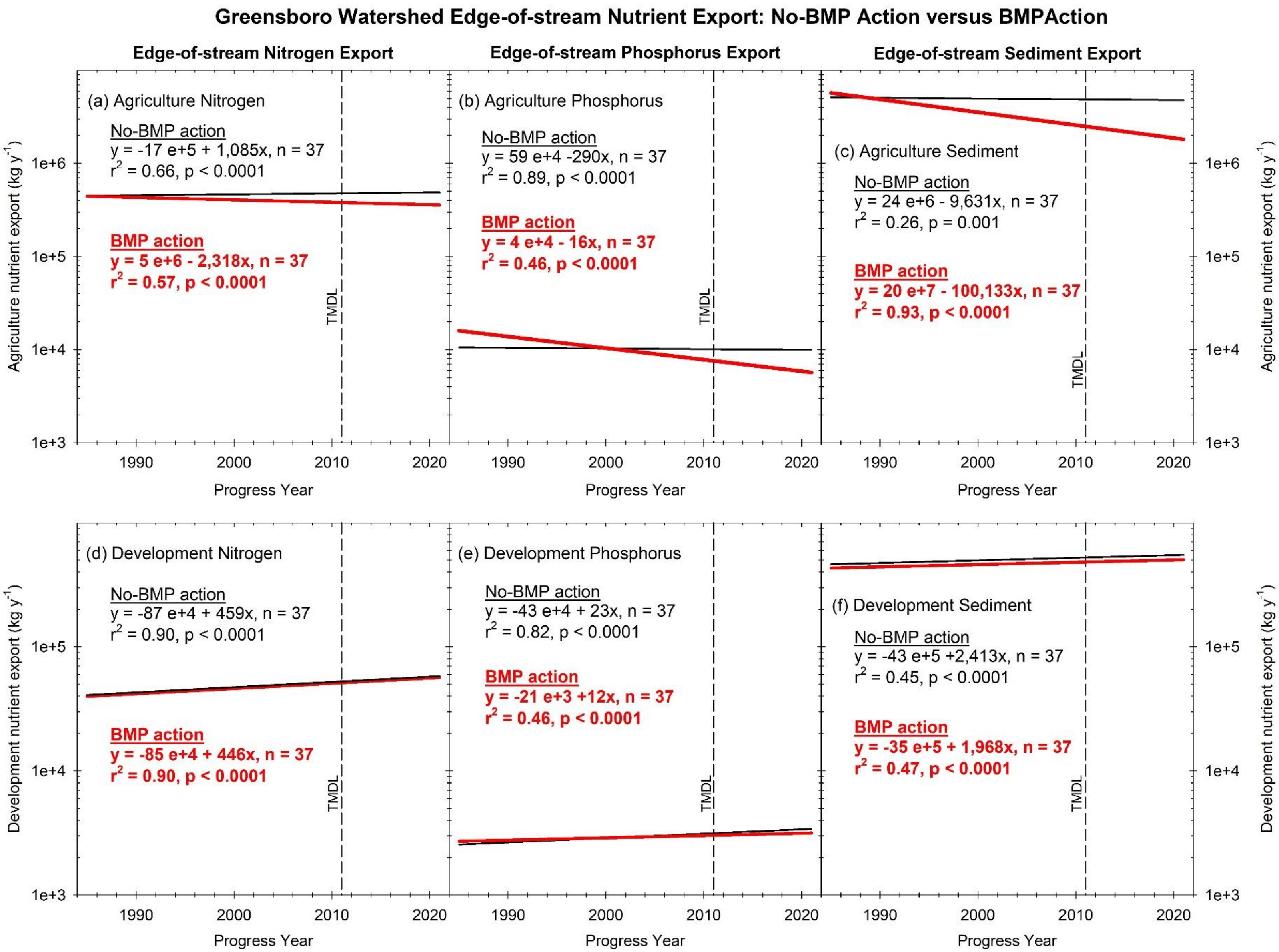


Figure 2.7. Modeled land-based edge-of-stream (EOS) nutrient export from the agriculture and development sectors within the Greensboro watershed. The No-BMP and BMP action trend lines shown in Figures 7d and 7e are too close to be seen individually.

Table 2.7. ANCOVA equal slopes test and Holm-Sidak comparisons of the difference of adjusted means. Abbreviations: "a" represents the y-intercept, "b" represents the slope, "Adj. $\bar{x}$" represents the adjusted mean, "se" represents the standard error, and "p" represents the p-value.

Figure	ANCOVA Group	a	slope (kg/y y^{-1})	Adj. $\bar{x}$	se	p
7d	Development N No BMP actions	-858,132	453	48,948	268	0.003
7d	Development N BMP actions	-859,309	453	47,771	268	
7f	Development TSS No BMP actions	-3,879,960	2190	506,993	4,333	< 0.001
7f	Development TSS BMP actions	-3,919,592	2190	467,361	4,333	

A subsequent analysis of the equal slopes models revealed that there is a significant difference in the adjusted means between the No-BMP action (adj. $\bar{x}$ = 48,948 ± 268, CI[48,414 to 49,482]) and BMP action (adj. $\bar{x}$ = 47,771 ± 268, CI[47,237, 48,305]) mean edge-of-stream N export ($t = 3.1$, $p = 0.003$). However, the differences were small, and the effect of BMP actions on the edge-of-stream N export was only 2.5 % lower than the No-BMP action scenario. An ANCOVA equal slopes test of the No-BMP action and BMP action for edge-of-stream TSS export shown in Figure 2.7f detected no significant differences ($b = 2190$ kg y^{-1}, Table 2.7). A subsequent analysis of the equal slopes models revealed that there is a significant difference in the adjusted means between the TSS No-BMP action (adj. $\bar{x}$ = 506,993 ± 4,333, CI[498,353 to 515,633]) and TSS BMP action (adj. $\bar{x}$ = 467,361 ± 4,333, CI[458,720, 476,001]). The effect of BMP actions on the edge-of-stream TSS export was 8 % lower than the No-BMP actions mean ($t = 6.5$, $p < 0.001$). The data shows that the No-BMP and BMP action scenarios have led to upward-trending edge-of-stream N, P, and TSS exports between 1985 and 2021. However, BMP actions led to significantly less N and TSS export than without BMPs, but the effects of the BMPs were minor (2-8%).

2.4.2 Greensboro watershed nutrient export in 2021

Despite significantly decreasing edge-of-stream N export from the agricultural sector, agricultural land uses contributed the largest percentage of N in the Greensboro watershed (Fig. 2.8). Agriculture comprised 47% of the land cover in the watershed, yet contributed 73% of N. The annual changes in N export from the watershed by agricultural BMPs were <10% (Fig. 2.7). In comparison, natural land uses such as forests and wetlands comprised 50% of the land cover in the watershed and contributed 84% of TSS to the Choptank River primarily due to stream bed and bank erosion (Fig. 2.8). Contributions to P export were due to relatively equal contributions from the natural and agriculture sectors. Small increases in nutrient export from the rural-urban development sector occurred between 1985 and 2021 (Fig. 2.7), and in 2021, contributed 15% of N (including septic systems), 18% of P, and 3% of TSS export (Fig. 2.8).

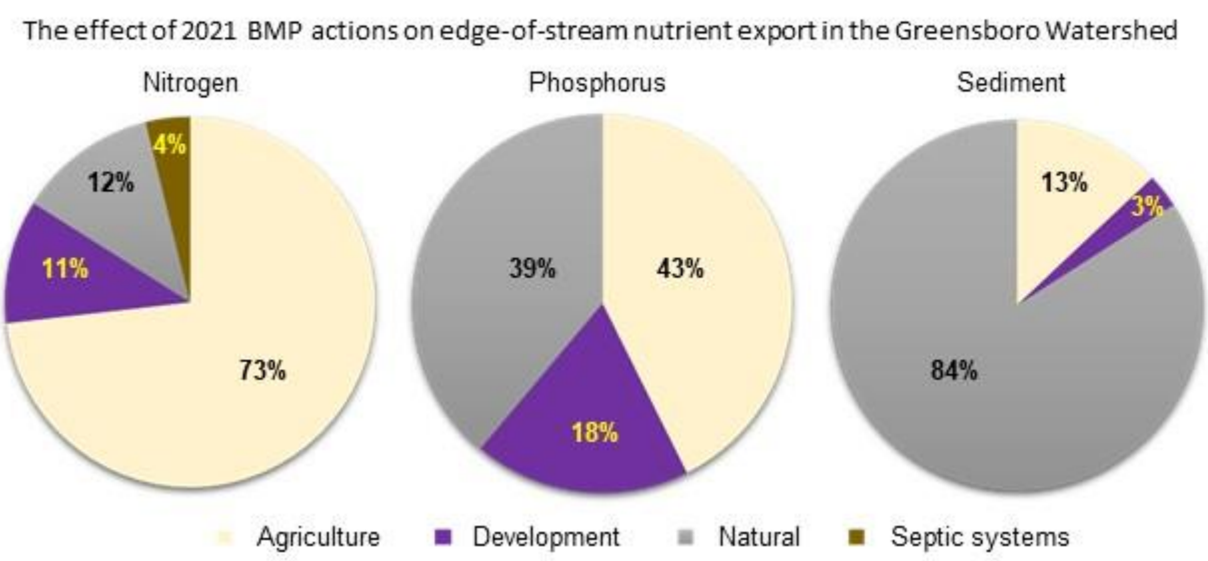


Figure 2.8. The nutrient export from each sector after BMP implementation in the progress year 2021.

2.4.3 2010 BMP actions versus 2021 BMP actions

A comparison between watershed-scale edge-of-stream nutrient export based on BMP actions in 2010 and 2021 revealed no change in N and a small increase in P. These changes were due to increased agriculture and development N exports and P export from the agriculture and natural sectors (Table 2.8). However, the modeled agricultural and natural BMP actions reduced TSS export in the Greensboro watershed by 14%. To review the nutrient export from load sources in each sector, see Appendix G. These data indicate no significant decrease in N and P export even though BMP implementation increased significantly in all sectors.

Table 2.8. Nutrient export based on land-based load allocations after BMP implementation in 2010 and 2021 in the Greensboro watershed. Abbreviations: "Greensboro watershed sectors" list the sector and pollutant, "2010 BMP action EOS export (kg)" represents the total edge of stream export due to BMP implementation in progress year 2010, "2021 BMP action EOS export (kg)" represents the total edge of stream export due to BMP implementation in progress year 2021, "Δ Export" represents the difference between 2010 BMP nutrient export and 2021 BMP nutrient export, and "Percent change" represents the increase or decrease of Δ export from 2010 BMP to 2021 BMP implementation.

Greensboro watershed: sector	**2010 BMP action EOS export (kg y^{-1})**	**2021 BMP action EOS export (kg y^{-1})**	**Δ Export (kg y^{-1})**	**Percent change**
Edge-of-stream total nitrogen export				
Agricultural TN	356,454	358,150	1,696	0%
Development TN	51,219	52,719	1,500	3%
Natural TN	60,446	59,672	-774	-1%
Septic TN	19,310	18,874	-436	-2%
SumTN	487,429	489,415	1,986	0%
Edge-of-stream total phosphorus export				
Agricultural TP	6,664	6,896	232	3%
Development TP	3,004	2,980	-24	-1%
Natural TP	6,240	6,287	47	1%
Sum TP	15,908	16,163	255	2%
Edge-of-stream sediment export				
Agricultural TSS	2,632,874	2,172,063	-460,811	-18%
Development TSS	463,773	495,486	31,713	7%
Natural TSS	16,514,459	14,114,058	-2,400,401	-15%
Sum TSS	19,611,106	16,781,607	-2,829,499	-14%

2.5 Discussion

2.5.1 Test of the hypothesis

The data presented above support the primary hypothesis that BMP implementation has increased significantly in the Greensboro watershed between 1985 and 2021. During this time, there were 133 unique varieties of BMPs installed in the watershed, and this included BMPs in agriculture (98), rural-urban development (23), septic system (5), animal (4), and natural (3) sectors. Additional statistical tests revealed many of the BMPs from all sectors increased significantly after the TMDL. Kleinman et al. (2019) also found that BMP implementation is widespread in the Chesapeake Bay watershed, and Zhuang et al. (2016) found BMP global expansion significantly increased from 2004 to 2013. Between 1994 and 2003, Zhuang et al. (2016) found much of the BMP research occurred in the United States. The dramatic response by stakeholders to implement BMPs in the Greensboro watershed to meet the Bay TMDL is an encouraging outcome for other TMDLs in the United States, such as in the Great Lakes basin in the Upper Midwest (USEPA 2023) and Neuse River watershed in North Carolina (Lebo et al. 2012).

A comparison between BMP implementation levels and No-BMP actions demonstrated that **agricultural BMP nutrient export** was trending downward; however, BMP implementation resulted in a faster rate of decreasing nutrient export from the watershed than without BMPs (Fig. 2.7). In contrast, No-BMP and BMP action scenarios revealed increasing trends for **rural-urban development nutrient export**. At the watershed scale, significantly decreasing agricultural nutrient export was offset by small increases in rural-urban development nutrient export. However, the nutrient export in 2021 from the agriculture sector was far greater than those from the rural-urban development sector. These results agree with Fisher et al. (2021), where the agriculture sector contributed little to water quality improvement in the Choptank River basin. In contrast, BMP implementation decreased 2021 TSS export compared to 2010 (Table 2.8). Still, additional stream bed and bank BMPs in the natural sector will be required to reduce the overall TSS export. A comparison between nutrient export in 2010 and 2021 revealed no difference in N and a small increase in P export, making these trends concerning for achieving the overall Bay TMDL goals. Yet, the modeled export results, particularly the 2021 nutrient export compared to the 2010 nutrient export, are concerning and raise questions regarding how these practices improve water quality. In the following paragraphs, I offer explanations for increasing BMP implementation and variable nutrient export at the watershed scale.

2.5.2 Factors that influence BMP adoption by farmers

Studies show farmers participating in outreach and technical assistance programs are more likely to implement sustainable agriculture practices, including BMPs. For example, adopting sustainable agriculture practices was higher among farmers who grew row crops, had irrigation facilities, and favored crop diversification (Mishra et al. 2018) or operated a large farm and owned a conservation easement (Doran et al. 2020). Mishra et al. (2018) and Doran et al. (2020) found that having a college education also positively and significantly affected the intensity of applying sustainable agriculture practices among farmers in Kentucky and the Northeast region of the United States. In contrast, farmers who were uninformed about sustainable farming and unfamiliar with technology were less likely to apply sustainable agriculture practices (Mishra et al. 2018). Bechini et al. (2020) also found that financial, technical, or social reasons prevented Italian dairy farmers from applying BMPs. However, the prevalent reason the dairy farmers did not use BMPs was because of the opinion of their trusted source of information on applying BMPs. Thus, to increase the widespread implementation of BMPs, environmental managers, policymakers, and program developers should support existing outreach and technical assistance programs and work to gain favor among the farmer's trusted social network and community members by promoting BMPs on demonstration farms or personal interaction in the community while demonstrating BMPs.

2.5.3 Funding supports agricultural BMP implementation

The history of BMP implementation in the Greensboro watershed revealed significant increases in many of the BMPs, especially after the TMDL. After the TMDL, funding mechanisms to support higher levels of agricultural BMP implementation increased. For example, in 2014, the Maryland Agricultural Water Quality Cost-Shore Program spent $27.3 million to fund the implementation of 2,370 BMPs (MASCD 2014). It helped make Maryland's cover crop program the most successful in the U.S. by increasing participation levels with higher payments (Wallander et al. 2021). In addition, the USDA recently announced an additional $22.5 million in the fiscal year 2022 to increase water quality improvement and conservation of agricultural BMPs in the Chesapeake Bay watershed, building on a $1.1 billion investment already made by USDA over the past decade (USDA 2022). Incentivizing farmers via higher payment amounts has positively expanded cover crop implementation in Maryland. Additional funds could support increased levels of agricultural BMP implementation needed to reduce nutrient export in the Chesapeake Bay watershed. Moreover, TMDL segments that require reductions in N by as much as 76% (e.g., CHOTF described in Appendix H) should be a higher priority to receive BMP funds.

Further dollar investments can also support compliance with existing regulations requiring nutrient management plans (NMP) for nearly all farms in Maryland and Delaware (Delaware 1999; Maryland 2015; Reimer et al. 2018). Many farmers in both states possess NMPs, test nutrient levels in soil and manure, and practice split applications of N fertilizer (Perez 2015). However, Perez (2015) also found that many farmers did not adopt other nutrient management practices, such as accounting for residual N from previous legume growth or manure application, maintaining manure-free setbacks alongside surface waters, avoiding winter manure applications, and frequently calibrating manure spreaders. Meeting nutrient management practices without oversight meant many aspects of the NMPs were voluntary. Additional funding could support the much-needed staffing to assist farmers with meeting NMPs.

2.5.4 Long-term water quality record USGS gauging station at Greensboro

Nutrient export from the Greensboro watershed contributed ≤ 10% of the N, P, and TSS to the total CHOTF export (Appendix H), and BMP implementation in 2021 resulted in no changes in N export, 2% increases in P export, and 14% decreases in TSS export compared to 2010 nutrient export after BMP implementation. These modeled N and P export reflect the upward-trending TN and TP concentrations revealed by the long-term USGS monitoring data (Fig. 1.3). Increasing TN and TP in the non-tidal portion of the Choptank River is the reason for concern as nutrient levels are approaching the nutrient criteria of 2.5 mg TN L^{-1} and currently exceed the nutrient criteria of 0.094 mg TP L^{-1} for healthy streams in Maryland (Morgan et al. 2013) and approaching the nutrient threshold values, 3.0 mg TN L^{-1} and 0.2 mg P L^{-1}, in Delaware (DNREC 2005). Additionally, BMP implementation downstream of the Greensboro watershed could be negated by increasing N and P in the Greensboro watershed, making the

CHOTF TMDL more challenging to achieve. The long-term water quality record could indicate that (1) there is insufficient BMP implementation in the watershed (Mulla et al. 2005; Sutton et al. 2010; Kroll et al. 2019), (2) implemented BMPs are malfunctioning or improperly maintained (Lintern et al. 2020), or (3) implemented BMPs are overwhelmed by added nutrients (Fisher et al. 2021). For this research discussion, I explore the possibility of implementing BMPs more suited to the soil environment in the Greensboro watershed and explore how functioning BMPs are overwhelmed by added nutrients in the following paragraphs.

2.5.5 Historical land cover infuences land-based BMP implementation

By 1900, deforestation combined with artificial drainage and ditching practices enabled the conversion of ~80% of the primary forested land to agricultural uses in the Choptank River Basin, and what forest land remained was unsuitable for housing and farming (Benitez et al. 2004; Fisher et al. 2006a; Needelman et al. 2007). However, predominantly poorly drained to well-drained soil types remained in the Greensboro watershed, which has moderately permeable subsoil of either clay loam to sandy loam or sandy loam to sandy clay loam (DNREC 2005). Combined with the watershed’s generally flat topography, the slow movement of groundwater through a hypoxic environment makes the soils more suitable for denitrification (Staver et al. 1998; MDE 2012). These poorly drained soils could decrease the N efficiency of BMPs, such as cover crops (Lee et al. 2016), making wetlands a more suitable choice for the Greensboro watershed. The modeled N, P, and TSS loading rates for wetlands are among the lowest in the Greensboro watershed (Table 2.9). Additionally, agricultural open spaces, characterized as unmanaged agricultural land that receives no manure, biosolids, fertilizer, or other nutrient

Table 2.9. Nutrient export rate with BMP actions in 2021. The load sources responsible for the lowest and highest nutrient export rate in each sector within the Greensboro watershed are summarized below. Abbreviations: **HF** = harvested forest, **LG** = leguminous hay, **MO** = mixed open, **NRTC** = non-regulated tree canopy, **OS** = open space, **P** = pasture, **PFS** = permitted feeding spaces, **RC** = regulated construction, **SC** = specialty crop, **TCTG** = MS4 tree canopy over turf grass, **W** = wetlands.

	Nitrogen (kg ha^{-1})		**Phosphorus (kg ha^{-1})**		**Sediment (kg ha^{-1})**	
Sector	Lowest EOS export	Highest EOS export	Lowest EOS export	Highest EOS export	Lowest EOS export	Highest EOS export
Agriculture	OS (4.6)	PFS (561.0)	LG (0.03)	PFS (23.2)	P (0.9)	SC (743.9)
Development	NRTC (8.7)	RC (30.4)	TCTG (0.6)	RC (3.0)	NRTC (56.2)	RC (384.2)
Natural	W (1.8)	HF (13.5)	W (0.03)	MO (0.4)	W (1.7)	MO (185.3)

applications, were among the agricultural sector's lowest N load sources partially because of wetlands (Appendix B). Other BMPs influencing agricultural open spaces' low N loading rate include forest and grass buffers (Weller et al. 2011), soil conservation and water quality plans, and water control structures (Strock et al. 2007; Carstensen et al. 2020). Increased use of these BMPs and expansion of agricultural open spaces with BMPs should be considered in future N management strategies.

Due to the density of agricultural drainage ditches in the Greensboro watershed, denitrifying bioreactors could be a treatment option to remove groundwater N from drainage water. Identifiable discharge points into bioreactors present an opportunity for quantifying N removal efficiencies through direct measurements of influent and effluent concentrations. In an agricultural drainage ditch, denitrifying bioreactors utilizing the standard woodchip substrate remove 35−50% of the influent at a rate of 2− 22 g^{-1} N m^3 d^{-1} and sustain their performance for at least 10 years (Stephenson et al. 2021). Thus, water quality management programs should incentivize farmers by offering low-cost implementation while gaining more certainty in N removal efficiency.

2.5.6 Nutrient inputs overwhelm existing management practices

Few animal BMPs have become responsible for safely storing increasing quantities of animal waste (Mostaghimi et al. 2001; Pickford 2022). Unfortunately, the animal waste management BMPs do not reduce nutrients but attempt to move the manure elsewhere. The data in Figures 2.6 (panels d-f) and the corresponding t-tests provided in Table 2.6 indicate more manure remained within the Greensboro watershed counties, Kent County, Delaware and Maryland counties, Queen Anne’s and Caroline, as manure transport remained unchanged and animal waste management nearly doubled. These findings are consistent with Keisman et al. (2018) and Chang et al. (2021). Additionally, the CAST data indicates manure N application rates in 2021 increased by 40%, and manure P application rates increased by 50% since the TMDL (Figure 2.9). Even though the land area receiving manure increased (Appendix I), there is still insufficient agricultural land to apply large amounts of manure at lower application rates (NRCS 2003).

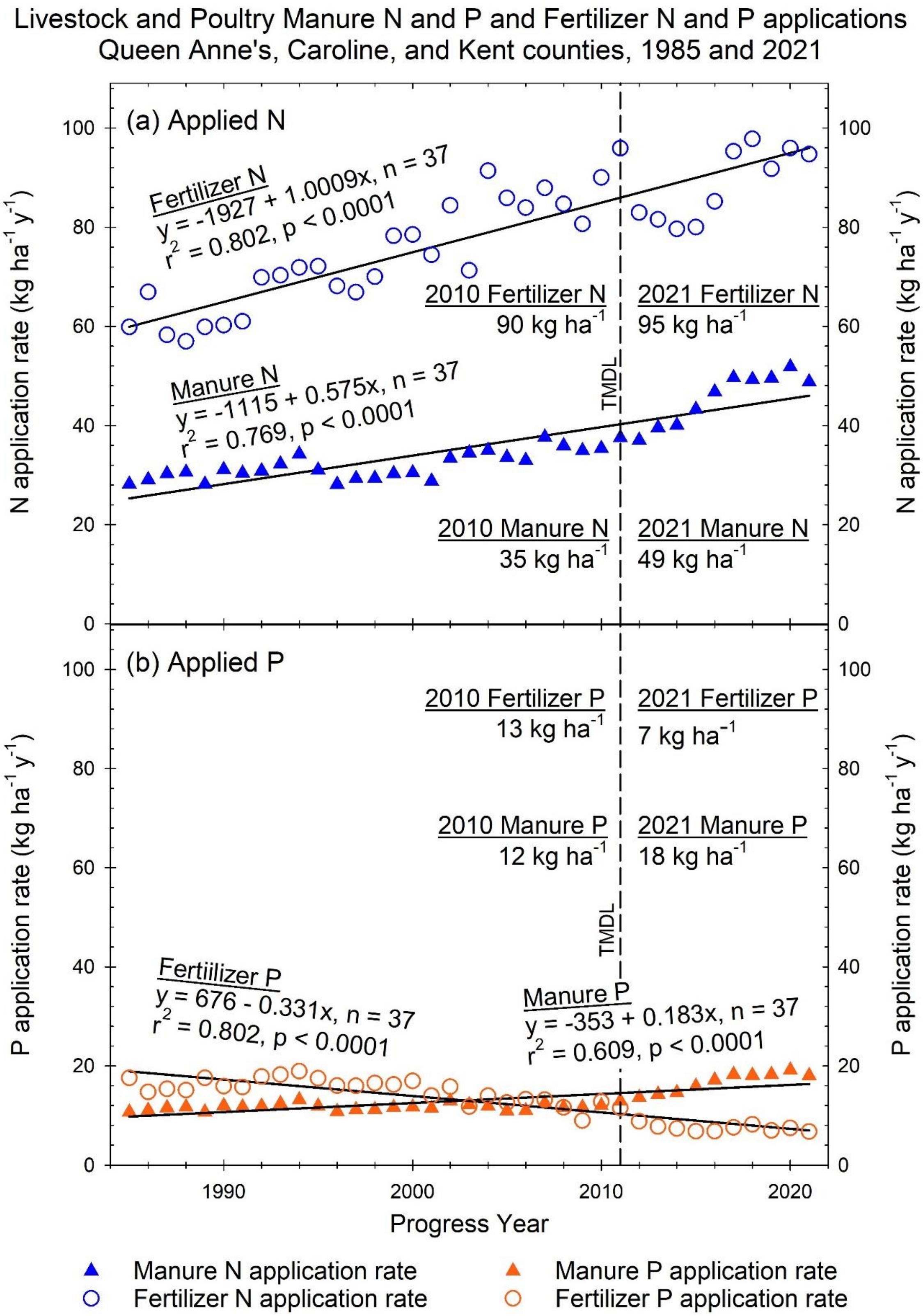


Figure 2.9. In Greensboro watershed counties, manure N and P and fertilizer N application rates increased as fertilizer P rate decreased from 2010 to 2021. Data source: CAST report on applied nutrients at the county level.

Due to volatile ammonia losses and denitrification, animal manure tends to be enriched in P relative to crop needs. Poultry manure, the major organic nutrient source on the Eastern Shore, contains plant-available N and P at a ratio (mass basis) that typically is less than two (Staver et al. 2001), while crops need approximately five times more N than P. As a result, applying poultry manure based on crop needs for N results in an application of P that is 3 to 4 times greater than will be removed in harvested crops. Conversely, applying poultry manure based on the P needs of a single crop requires spreading manure across a much larger land area, and the supplemental N can be applied as commercial N (Simpson 1991). Figure 2.9 offers evidence supporting that increased application rates of manure and fertilizer N likely contributed to increased N export, negating the positive N-reducing capacity of BMPs. Similarly, Fertig et al. (2014) found elevated levels of N attributed to increased applications of chicken manure equivalent to 263% and 57% of N generated by the human populations in the Monie Bay watershed and Wicomico River watershed, respectively, which drain portions of southern Delmarva. Moreover, conservative estimates revealed the poultry population in Delmarva generated an amount of N equivalent to 76% of the amount generated by the actual human population (Fertig et al. 2014).

USGS watershed gauge near Greensboro, Maryland

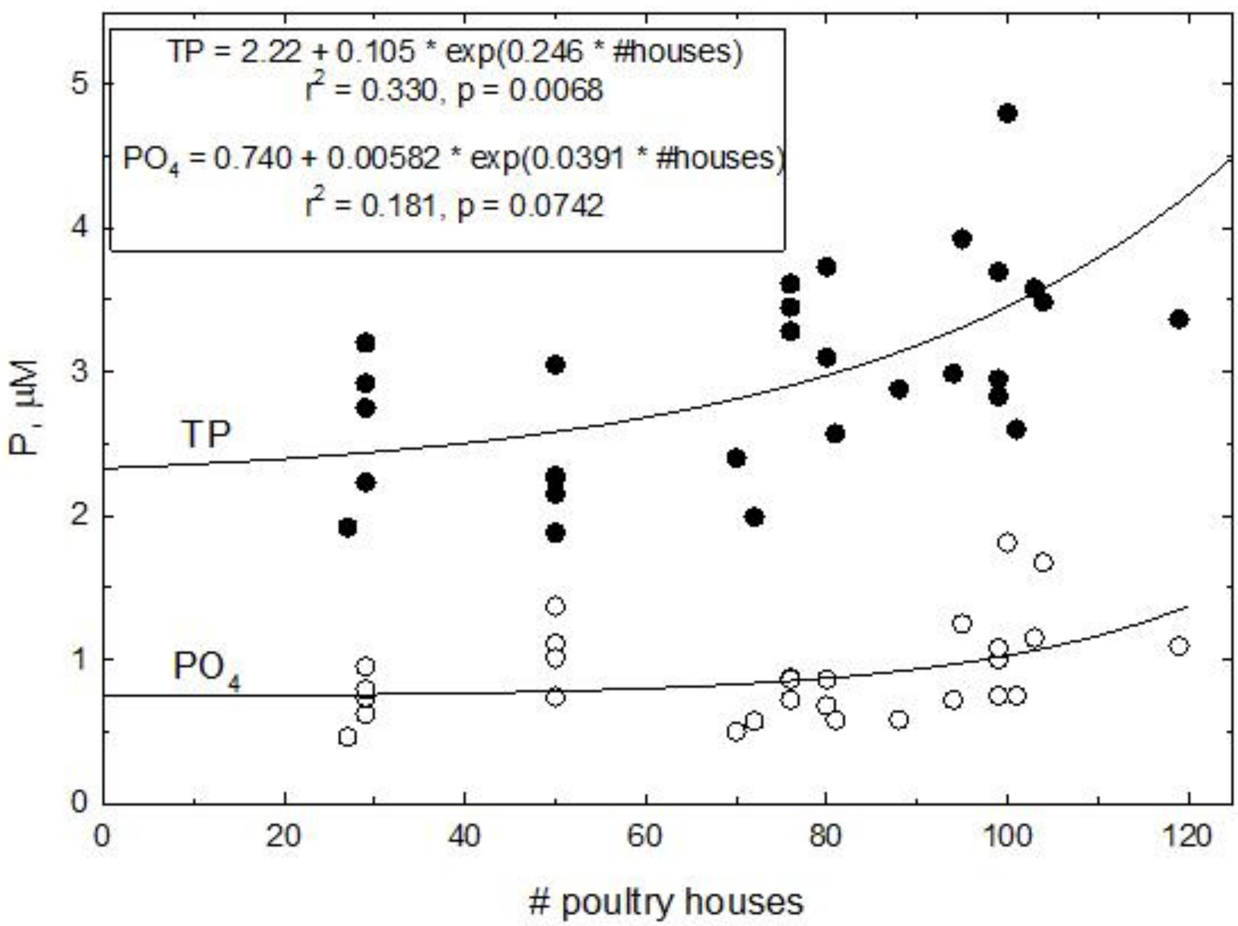


Figure 2.10. TP and PO_4 concentrations and numbers of poultry houses in watersheds within the Choptank River Basin (Source: Silaphone and Fisher, unpub).

Additionally, a study by Amato et al. (2020) found that N concentrations increased up to three times higher in watersheds with the highest poultry house densities than without poultry houses on the Delmarva Peninsula. This same study found that P concentrations were not correlated with poultry house density (Amato et al. 2020). In contrast, Silaphone and Fisher (unpub.) found that both TP ($p < 0.01$) and PO_4 ($p = 0.07$) at the Greensboro watershed gauging station have exponentially increasing relationships with the number of poultry houses (Figure 2.10) and Figure 2.9 illustrates manure P application rates have increased between 1985 and 2021, increasing by 50% from 2010 to 2021.

These data suggest other drivers have influenced PO_4 concentrations, such as functioning BMPs being overwhelmed by added nutrients (Sutton et al. 2010; Fisher et al. 2021; Longo et al. 2021), and recent research emphasizes the need to reduce inputs over attempts to manage nutrient transport and use (Ator et al. 2020). For example, Lucas et al. (2021) found that soil water-extractable P declined significantly over nine years after ceasing manure or fertilizer P cropland applications. Overall, the BMP data clearly shows no significant changes in manure transport after the TMDL. Yet, animal waste management BMPs (Fig. 6, Table F5) and manure P and N cropland applications (Fig. 9, Appendix I) have increased significantly between 1985 and 2021, indicating more needs to be done to address manure inputs into the Greensboro watershed.

2.5.7 Climate change impacts on management practices

Global average temperatures have risen since the 1950s (Lobell et al. 2011), and increasing air temperatures and changes in precipitation patterns and intensity are anticipated throughout the U.S. over the 21st century (Melillo et al. 2014). Climate change modeling suggests in the U.S. Northeast, BMPs designed to mitigate nonpoint source pollution in the current climate will be insufficient to achieve water quality goals with projected climate change (Renkenberger et al. 2017). Climate change is expected to increase temperature, annual rainfall, and storm intensity, increasing surface runoff, streamflow, sediment, and P export (Giri et al. 2020). In response, BMPs must be more widespread, and current pollutant hotspots will generate excess amounts of new nutrients that will require re-design of existing BMPs (Renkenberger et al. 2016; Renkenberger et al. 2017).

2.6 Agronomic recommendations

- Higher payments are needed to incentivize the installation of BMPs suited to hydrogeomorphology in the Greensboro watershed.
- Develop outreach programs to gain community support for widespread agricultural BMPs.
- Allocate BMP funding in TMDL segments having to reduce nutrient export by a significant percentage, such as the 76% N reduction needed in the CHOTF to achieve the land-based load allocation.
- Explore manure management options, including reducing manure N and P applications onto agricultural cropland, applications of supplemental manure onto alternative vegetative covers outside the agriculture sector, and publicly funded manure transport programs to immediately remove manure from surplus areas to deficit areas.
- Research is needed to understand how to adapt existing BMPs and future BMPs to a changing climate.
- Explore BMP nutrient removal performance and if the efficiencies are adequately tested.
- Evaluate factors influencing modeled N and P nutrient export.

Chapter 3: An Assessment of cover crop nitrogen efficiencies in the United States Coastal Plain, 1980 – 2022

Abstract

Cover crop best management practices (BMPs) are widely implemented in the Chesapeake Bay watershed to intercept agricultural field losses of nitrogen (N) and phosphorus (P) that have fueled eutrophication in the Chesapeake Bay and fresh, estuarine and coastal waters globally. My assessment focused on cover crop studies in the United States Coastal Plain province published between 1980 and 2022. I evaluated 689 N efficiencies from 18 cover crop studies to test the hypothesis that cover crop BMP efficiencies have an adequate basis for estimating their capacity to intercept N. To test this hypothesis, I conducted the following cover crop assessment: (1) identified multiple N efficiency calculation approaches, (2) quantified cover crop N efficiencies, (3) summarized common variables identified in the literature that influenced the reported cover crop N efficiencies, and (4) identified limitations that may have impacted cover crop N efficiencies. Cover crop N efficiency was calculated as the ratio of an N interception by cover crop biomass or a reduction in soil or groundwater N divided by an N input, e.g., previous spring fertilizer or a previous soil or groundwater N concentration or flux. The use of these variables resulted in wide ranges in mean cover crop N efficiency (7-86%) due to empirical and modeling experimental approaches, varying methods, and parameters used to calculate efficiency. The modeling approach generally resulted in N efficiencies significantly higher than the empirical approach, as did the parallel control-treatment experiments compared to the sequential before-and-after implementation method. Results indicated the cover crop N efficiencies based on soil residual N were greater than N efficiencies based on cover crop biomass immobilization. In turn, cover crop N efficiencies based on immobilization studies were

greater than N efficiencies based on groundwater nitrate studies. Because there is no standard methodology to report the effect of cover crops, standardized metadata describing the variables used in the N efficiency calculations should accompany future reported cover crop N efficiencies.

3.1 Introduction

3.1.1 Eutrophication

Frequent instances of eutrophication in fresh, estuarine, and marine waters globally are fueled by nitrogen (N) and phosphorus (P) enrichment (Howarth 2008; Schindler et al. 2008; Smith et al. 2009; NRC 2011; Lankoski et al. 2013; Foucher et al. 2020; Wang et al. 2021). Sources of increasing nutrient inputs are associated with global wastewater discharges in urban areas (Gücker et al. 2006; Carey et al. 2009; Fisher et al. 2021) and the inefficient use of applied fertilizer on agricultural fields by crops (Staver 2001; Canfield et al. 2010; Swaney et al. 2018; Swaney et al. 2019). Studies show that as fertilizer applications increase globally, the global N use efficiency (NUE), defined as the percent of applied N fertilizer removed by harvested crop products (Cassman et al. 2002), decreased from 68% in the early 1960s to 42% by 2010 (Erisman et al. 2011; Lassaletta et al. 2014; Zhang et al. 2015b). Likewise, the estimated P use efficiency (PUE), also defined as the percent of applied P fertilizer removed by harvested crop products, is less than 15% worldwide (Suh et al. 2011; Johnston et al. 2014; Roberts et al. 2015; Lun et al. 2018; Scholz et al. 2018). Across the U.S., NUE decreased from 49% in 1987-1997 to 45% in 2002-2012 due to crop production not increasing as fast as higher applications of N fertilizer, sometimes above crop N requirements, resulting in unused N in the field (Swaney et al. 2018). The PUE in the U.S. Southeast (mid-Atlantic to Mississippi River) is typically less than 30% (Blackwell et al. 2019).

The inefficient use of applied N and P threatens coastal waters and jeopardizes global crop production and food security as the human population grows (Howden et al. 2013; Yuan et al. 2017). For example, future climate change will cause greater NUE reductions in northwest China (wheat: 43%; maize: 34%) than in the northeast (maize: 4%), which increases N losses to the environment (Liang et al. 2019). Liang et al. (2019) also show maize and wheat yields in northwestern China decreased by -31% and -16%, respectively, and slightly increased by 6% in northeastern China. Clearly, decreasing NUE and declining crop yields are concerning for China, which currently has the world's second largest human population (1.4 billion per United Nations).

Another potential source of nutrient loss downstream and future crop use is the release of applied fertilizers via crop residue decomposition that remains on cropland after harvest (Lee et al. 2016). The decreasing NUE and low PUE of cash crops leave excess N and P on agricultural fields after harvest, which can be exported to surface waters through multiple pathways such as overland flow and groundwater (Staver 2001). The nutrient export via overland flow and groundwater can cause coastal and freshwater eutrophication, the most common water quality response to nutrient over-enrichment of aquatic systems (Canfield et al. 2010). Yet, the degradation of fresh, estuarine, and coastal waters is not inevitable with better farm management.

3.1.2 Best management practices

Today, agricultural best management practices (BMPs) are the primary tool used to prevent eutrophication in rural areas (Staver et al. 1998; Inamdar et al. 2001; Stone et al. 2004; Cullum et al. 2006; Amblard 2012; Liu et al. 2017b; Xue et al. 2020; Smalling et al. 2021). For example, Hughes et al. (2014) observed mixed effects on water clarity during a 13-year period where cattle were excluded from riparian areas and trees and shrubs were planted on mostly degraded land in the headwater catchment in the western Waikato region of New Zealand. Rapid improvements to stream water clarity were attributed to the removal of cattle from riparian areas without additional riparian vegetation. In contrast, poorer water clarity was attributed to soil erosion due to the lack of ground cover vegetation in riparian areas planted with trees and shrubs, even as livestock were excluded from riparian areas (Hughes et al. 2014). Strauch et al. (2013) modeled sediment reductions of up to 40% by implementing parallel terraces and small sediment basins in the catchment of the Pipiripau River in Brazil, where urban sprawl and intensive agriculture have contributed to nonpoint source pollution to the region's water resources. Still, higher sediment yield reductions ranging from 70% to 80%, modeled by Uniyal et al. (2020), were attained by applying a mixture of cultural and structural agricultural BMPs in the Baitarani River basin in India. In contrast, Lee et al. (2023) modeled soil loss reduction to be as low as 8%, and suspended soils reduction was as low as 7% in the agricultural, mountainous Soyang River watershed, South Korea, due to slope length and precipitation events making soil erosion more challenging to manage (Sinha et al. 2017).

Modeling and empirical studies applied across the United States show combinations of cultural and structural agricultural BMP applications reduce, intercept, or prevent the export of suspended sediment and agricultural N and P before reaching receiving waters (USEPA 1993a; Dukes et al. 2003; Cullum et al. 2006; McCarty et al. 2008; Hanson 2018; Gharibdousti et al. 2019). Examples of cultural BMPs, such as conservation tillage, crop rotation, and fertilizer management, and structural BMPs, such as a controlled irrigation system, denitrifying bioreactors, and water control structures, can decrease N and P field losses (Davidson et al. 2015; Rosen et al. 2017; Carstensen et al. 2020; Fixen 2020).

The water quality benefit from implementing agricultural BMPs is why the United States Environmental Protection Agency, state environmental agencies, and the United States Department of Agriculture advocate for the use of agricultural BMPs. For example, in the Chesapeake Bay watershed, BMPs are widely implemented in an attempt to improve water quality in the largest estuary in North America (Boesch 2006; Sutton et al. 2009; Fanelli et al. 2019; Harding et al. 2019; Sekellick et al. 2019; Ator et al. 2020; Hively et al. 2020). After the EPA approved the Chesapeake Bay TMDL in December 2010, agricultural BMP implementation nearly doubled between 2010 and 2014 due to increased applications of precision rotation grazing, precision agriculture, land retirement, and cover crops (NRC 2011; Hanson 2018; Sekellick et al. 2019). However, once farmers implement agricultural BMPs, a problem faced by many farmers is that the agricultural BMPs are not 100% efficient (USEPA 1993a; NRC 2011), and BMPs are rarely monitored; thus, some of the applied N and P not harvested by crops is available for export from agricultural fields with BMPs.

3.1.3 Measuring nutrient removal capacity

A clear, long-term water quality improvement strategy is to increase NUE and PUE by crops and the efficiency of agricultural BMPs. However, my research scope is limited to agricultural BMP efficiencies. Agricultural BMP efficiency is defined as a BMP's capacity to reduce nutrient or sediment export from farm fields and can be measured directly from the BMP, the water quality response, or soil nutrient content (USEPA 2002), as shown in the conceptual model in Figure 3.1.

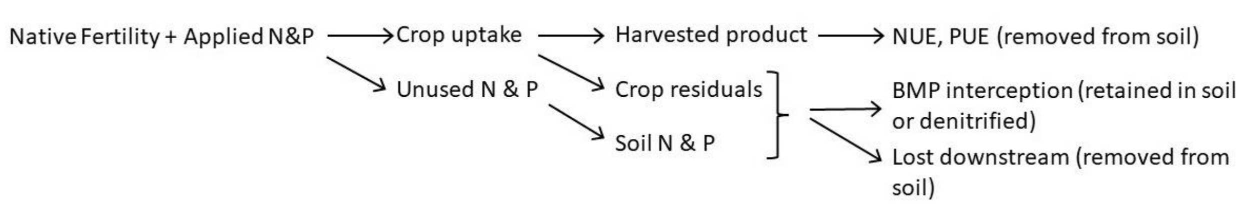


Figure 3.1. Conceptual model of the relationship between N and P availability, NUE, PUE, and BMP interception, and downstream losses from agricultural fields. Source: Fisher 2023, unpub.

There are two BMP efficiency formulae used to calculate the BMP efficiency. Equation 1 defines the BMP efficiency (E_{BMP}) as a percent of the previously applied N or P fertilizer (A) that is captured or immobilized by a BMP (I).

$$E_{BMP} = (I_{(t+1)} / A_t) * 100 \% \qquad \text{(eq. 1)}$$

where E_{BMP} = BMP efficiency (%) and represents the percentage of the applied N or P fertilizer captured or intercepted by the BMP, I = N or P immobilized by the BMP (kg ha^{-1} y^{-1}), and A_t = N or P fertilizer inputs (kg ha^{-1} y^{-1}) previously applied on the cropland during the growing year (Shipley et al. 1992).

Equation 2 describes the BMP efficiency (E_{BMP}) in parallel measurements of similar areas with and without BMPs or compares N and P losses before and after BMP implementation in sequential measurements in the same field as the change in N or P field losses without BMPs (L_C, control field) and with BMPs (L_{BMP}, treatment field):

$$E_{BMP} = 1 – (L_{BMP}/L_C) * 100 \% \qquad \text{(eq. 2)}$$

where E_{BMP} = BMP efficiency (%), L_{BMP} = Nutrient pathways (N or P export, soil N or P inventory, or groundwater nitrate in the field) with BMP implementation (kg ha^{-1} y^{-1}), and L_C = Nutrient pathways without BMP implementation (kg ha^{-1} y^{-1}) (Lowrance et al. 1997; Dukes et al. 2003; Lee et al. 2016).

3.1.4 Research purpose

Although BMPs have been applied around the world, there has been much concern regarding their efficiency in improving water quality (Xie et al. 2015; Stephenson et al. 2021), and when future climate change is taken into account, the nutrient removal ability of BMPs is expected to decline (Schmidt et al. 2019). There is a need to assess BMP efficiency case studies to identify common variables that influence N and P efficiencies to minimize the uncertainties. For example, many of the current cover crop review papers assessed variable cover crop impacts (Rivière et al. 2022), benefits to soil health (Hallama et al. 2018; Farmaha et al. 2022; Koudahe et al. 2022), and the broader impacts on water quality (Christianson et al. 2017b; Abdalla et al. 2019) at variable geographic scales that range from as small as the southeastern United States to global in extent (Table J1). However, these review papers do not report the percentage reduction of nutrient export from croplands due to cover crops.

For my research, I assessed the cover crop literature to quantify BMP efficiencies and associated variables that influence N and P efficiencies in the U.S. Coastal Plain Province. This province represents a unique opportunity to assess cover crop impacts on water quality in a region with a history of intensive agricultural activity (Kleinman et al. 2015; Glibert 2020). The combination of relatively high N and P inputs and use of irrigation for crop production coupled with its unique climate and soil morphology are conducive to surface and groundwater NO_3^- and P movement (Phillips et al. 1993; Hubbard et al. 2004; Kleinman et al. 2015). Consequently, large portions of the Coastal Plain have a high potential for N and P contamination of surface and ground waters (Bohlke et al. 1995; Staver et al. 1996; Hubbard et al. 2004; Harden 2015). Many studies have established a link between intensive agriculture and coastal eutrophication in the Coastal Plain (Mozaffari et al. 1994; Nino de Guzman et al. 2012; Kleinman et al. 2015;

Keisman et al. 2018; Brown et al. 2020), and efforts are underway to remediate degraded water quality via nutrient reduction goals outlined in the Chesapeake Bay TMDL (Ator et al. 2020) and through the ongoing development of TMDLs for the Cape Fear River watershed in North Carolina (NCDENR 2022).

In this thesis chapter, I focused on cover crop BMPs to provide a well-researched example of the factors governing N efficiency in the U.S. Coastal Plain Province. Cover crops are widely implemented in the Chesapeake Bay watershed, and the average ha of cover crops planted per farm in Maryland and Delaware are among the highest in the US (USDA 2017). My research tested the following hypothesis:

> Cover crop BMPs have an adequately tested basis for estimating their efficiency in the U.S. Coastal Plain Province.

To test the hypothesis, I reviewed the agricultural BMP efficiency literature. Overviews of the literature are provided to address the following research questions:

1. Is cover crop efficiency adequately measured?
2. What are the reported limitations of cover crop management practices?

3.2 Methods

3.2.1 Study area: United States Coastal Plain province

This review is focused on the agricultural implementation of cover crops in the U.S. Coastal Plain Province (Fig. 3.2) (Fenneman et al. 1946; Faulkner et al. 2011). There are six subregions within the Coastal Plain Province: Embayed, Sea Island, Floridian, West Gulf, East Gulf, or Mississippi Alluvial (Miller et al. 1994). At the subregion scale, the elevation range is classified by zones of Uplands (30 – 244 m), Transition (23 – 183 m), and Lower (<30 m) (Miller et al. 1994). The climate is mainly humid subtropical, but the region may be temperate north of Virginia. Soils range from finer-textured, nutrient-rich soils to nutrient-deficient, sandy soils; thus, water infiltration rates vary widely (Lowrance et al. 1997). Soil types can be classified into hydrologic soil groups (HSG) A, B, C, or D to indicate degrees of drainage from well-drained, moderately well-drained, moderately poorly drained, and poorly drained soils, respectively (Phillips et al. 1993; USDA 2007; Koskelo et al. 2018). Overall, the region has a mean annual temperature range of 12.8 to 21°C, and rainfall is well-distributed throughout the year, with an average precipitation range of 101 to 152 cm yr^{-1} (Lowrance et al. 1997; Fisher et al. 2010; Nagy et al. 2011; Hively et al. 2020).

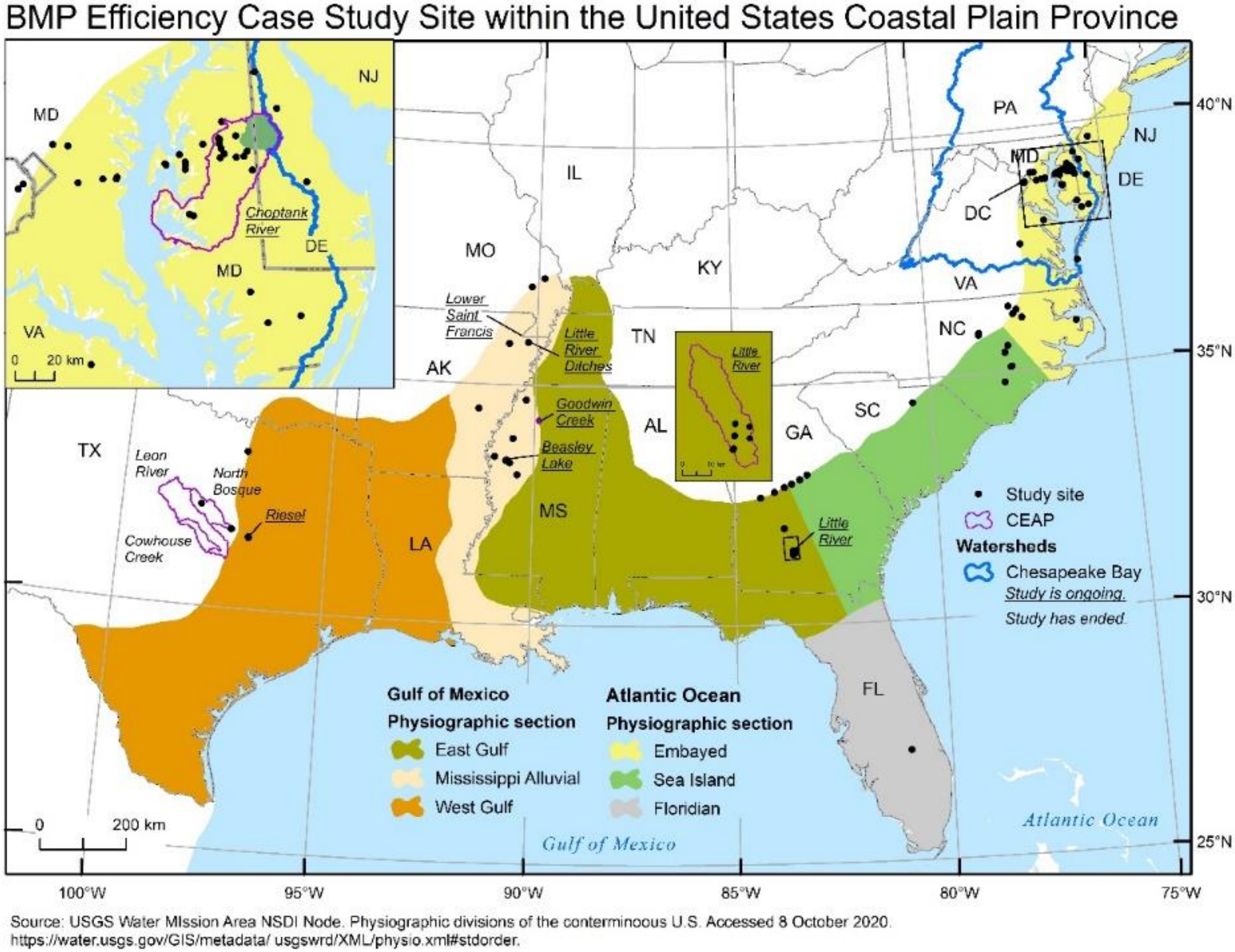


Figure 3.2. The U.S. Coastal Plain Province stretches from western Texas along the Gulf of Mexico and Eastern seaboard to its northern-most extent in southern New York state

3.2.2 Literature selection

This review paper is not a comprehensive, global review of agricultural BMPs but a concise review of cover crop BMP efficiency case studies in the U.S. Coastal Plain Province. The initial literature review searched for agricultural BMP efficiency studies in the U.S. Coastal Plain Province published between 1980 and 2022. I searched for peer-reviewed papers, government documents, and conference papers using the Salisbury University library search engine to access libraries worldwide and numerous databases. Results came from Proquest, Science Direct, EBSCO, PubMed, BioOne, JSTOR, Scopus, SpringerLink, WorldCat, Science.gov, and Google Scholar. To compile the agricultural BMP literature, I used variations of the following keywords: “best management or conservation practice,” “BMP,” “efficiency,” “effectiveness,” “nutrient load or concentration,” “nitrogen,” “phosphorus,” “agriculture,” “Chesapeake Bay,” “Delmarva,” “Choptank River,” “Southeastern U.S.,” “Greensboro watershed,” “CEAP,” “water quality,” “TMDL,” and “coastal.” I searched the title, abstract, and results section for keywords in each paper. Study sites were geo-located based on each paper’s coordinate information or an image reference using ArcGIS 10.8.1 or Google Earth. If a location was indiscernible, an approximate location was based on a place name referenced in the paper. The U.S. Coastal Plain Province GIS file was provided by the USGS and is based on the original work of Fenneman et al. (1946). I conducted this literature review between 2015 – 2017 and 2020 – March 2023. See Table 3.1 for a list of selected cover crop studies and study site characteristics.

Table 3.1. Eighteen cover crop studies in the U.S. Coastal Plain Province were selected for this assessment. Abbreviations: "**Paper ref**" = the paper referenced in this assessment and denotes modeling studies in bold text, "**Coord**" = geographic coordinates of the study location, "**Site**" = the name of study location, "**Basin**" = the river basin containing the site, "**Sub-St**" = subregions (Sub) within the Coastal Plain Province such as Embayed (Em), East Gulf (EG), Mississippi Alluvial (MA), Sea Island (SI), West Gulf (WG), and also the state (St) which is limited to Arkansas (AR), Georgia (GA), Delaware (DE), Maryland (MD), North Carolina (NC), Texas (TX), "**Scale (ha)**" = plot (Pl), field (F), SW (small watershed), or LW (large watershed) spatial scale followed by the cover crop treatment area in hectares, "**Length**" = the length of the study, "**Met**" = empirical (E) or modeling (M) approach followed by the experimental methods before-after (BA) or control-treatment (CT) used in the study, "**N path**" identifies N immobilized in cover crop biomass (I) and N loss pathways such as the soil column (Sc), groundwater export (Gw), direct pathways includes overland flow, lateral flow, and groundwater leachate (D), and overland flow (O), "**CCSp**" = to the cover crop plant species such as Annual ryegrass (*Lolium multiflorum Lam*.) (AR), Barley (*Hordeum vulgare* L.) (B), Black oats (*Avena strigosa* L.) (BO), Cereal rye (*Secale cereale* L.) (CR), Crimson clover (*Trifolium incarnatum* L.) (CC), Hairy vetch (*Vicia villosa* Roth) (HV), Cover crop mix includes a mixture of legume and non-legume or two or more non-legumes grown in one confined treatment area (Mix), Forage radish (FR, *Raphanus sativus*), Triticale (*Triticum secale* L.) (T), Winter wheat (*Triticum aestivum* L.) (WW), "**Sow**" = the Julian date seeds were sown and "**Sam**" = the Julian date N measurements were taken, "**Hyd-HSG**" = the presence of (Y) or absence (N) of hydric soils and the hydrologic soils group (HSG) such as well-drained (A), moderately well-drained (B), moderately poorly drained (C), and poorly drained (D), and "**Till**" = the tillage type such as no-till (NT), low-till (LT), reduced-till (RT), plowed seedbed (P), conventional-till (CV), Average N efficiency based on NT and CT (AT), and tillage type not reported by paper reference (n/a).

Paper reference	Coord	Site	Basin	Sub-St	Scale (ha)	Length	Met	N path	CCSp	Sow	Sam	Hyd-HSG	Till
Shipley et al. 1992	38.35, -75.78	Salisbury Poplar Hill Research Farm	Nanticoke	Em-MD	Pl (0.007)	1986-1988	E-BA	I	AR, CR, CC, HV	265-278	74-137	Y-B	NT
Ranells et al. 1997	35.30, -77.57	Lower Coastal Plain Tobacco Research Station	Neuse	SI-NC	Pl (0.25)	1992-1994	E-BA	I, Sc	Mix, CR, CC, HV	280	74-349	Y-A	NT
Ritter et al. 1998	38.64, -75.46	Uni. of DE Research and Education Center	Deep Creek	Em-DE	Pl (0.01-0.25)	1989-1991	E-BA+CT	I, Gw, Sc	CR	267-298	105-349	N-AB	AT, CV, LT
Staver et al. 1998	38.94, -76.15	Uni. of MD Wye Research and Education Center (Wye)	Wye	Em-MD	Pl (0.07) F (0.50)	1984-1996 1988-1994 1988-1996 1989-1996	E-BA+CT	I, Gw, Sc	CR	289-291	74-75	N-ABD	CV, NT
Coale et al. 2001	38.92, -76.15	Wye	Wye	Em-MD	Pl (0.01)	1996-1998	E-BA	Sc	B, CR, T, WW	287-297	105-192	Y+N-B	NT
Sainju et al. 2005	32.53, -85.89	Fort Valley State Uni. Agricultural Research Station Farm	Altamaha	EG-GA	Pl (0.01)	1993-2002	E-BA	I	Mix, CR, HV	298-299	105-106	N-A	AT, CV, LT

Table 3.1 (continued). Selected cover crop studies in the United States Coastal Plain province.

Paper reference	Coord	Site	Basin	Sub-St	Scale (ha)	Length	Met	N path	CCSp	Sow	Sam	Hyd-HSG	Till
Clark et al. 2007	38.35, -75.84	Salisbury Poplar Hill Research Farm	Nanticoke	Em-MD	Pl (0.001)	1989-1991	E-BA	I	CR, HV	279	74-135	Y-B	P
Sadeghi et al. 2007	39.05, -75.95	German Branch watershed (GBW)	Choptank	Em-MD	SW (5000)	1991-1995	M-CT	D	WW	291	120	N-A	n/a
Yeo et al. 2014	39.06, -75.95	GBW	Choptank	Em-MD	F (11.8) SW (5000)	1992-2000	M-CT	D, Gw	B, CR, WW	277-306	75	Y-BC	NT
Komatsuzaki et al. 2015	35.40, -78.03	Center for Environmental Farming Systems	Neuse	Em-NC	Pl (0.0014)	2000-2001	E-BA	I	BO, CR, T, WW	298-362	75-127	N-A	n/a
Lee et al. 2016	38.97, -75.80	Tuckahoe Creek (TC) and Greensboro watersheds	Choptank	Em-MD	LW (22070, 29010)	1999-2008	M-CT	Gw	B, CR, WW	277-366	75	Y-CD+AB	NT
Meisinger et al. 2017	39.02, -76.92	Beltsville Agricultural Research Center (BARC)	Anacostia	Em-MD	Pl (0.04)	1994-1997	E-CT	Gw	B, CR, WW	280-289	135-136	N-A	n/a
Aryal et al. 2018	35.87, -90.22	Mississippi Delta of AR	Mississippi	MA-AR	F (19.15)	2011-2014	E-CT	O	BO, WW	296	105	Y-CD	CV
Fisher et al. 2018	38.97, -75.85	Dukes Farm (private farm)	Choptank	Em-MD	F (3.4-16.2)	2012-2014	E-CT	Gw	B, Mix, WW	273-289	136	N-A	n/a
Hively et al. 2020	38.97, -75.94	TC watershed	Choptank	Em-MD	LW (22500)	2008-2017	M-CT	Gw	B, CR, WW	276-307	74-75	Y-CD	NT
Smith et al. 2020	31.47, -96.89	Riesel watershed	Brushy Creek	WG-TX	F (4-8.4)	2009-2013	E-CT	O	Mix	288	74	N-C	RT
Gaimaro et al. 2022	39.03, -76.84	Uni. of MD Central MD Research and Education Center	Patuxent	Em-MD	Pl (0.0003)	2016-2018	M-CT	Gw, Sc	Mix, CR, FR	265-290	74-349	Y-B	NT
Sedghi et al. 2022	39.03, -76.93	BARC	Anacostia	Em-MD	Pl (0.01)	2016-2018	E-CT	Gw, Sc	Mix	265-289	135	N-A+AC	NT

Based on my initial literature review, eighteen cover crop studies were selected for this assessment. The basis of reported N and P efficiencies in the studies is nutrient data before-and-after cover crop planting or conducted cover crop experiments comparing a control without cover crops with a cover crop treatment. Two additional BMP efficiency assessments of stream buffers and wetlands will be completed post-thesis.

3.2.3 Application of cover crop nitrogen efficiency formulae

Before-and-after (BA) and control versus treatment (CT) experimental methods are the basis of many cover crop studies. Equations 1 and 2 have been adapted to either method to quantify N efficiency, and Table 3.2 lists equation 1 and 2 formulae variations applied in BA experiments used in empirical studies. The BMP efficiency equation 1, $E_{BMP} = (I_{(t+1)} / A_t) * 100$ %, was applied to seven cover crop immobilization studies where the numerator (N pathway) is the spring measurements of N content in cover crop biomass and the divisor (N input) is the previous spring cash crop fertilizer N or the previous fall soil residual N. An exception to the BA immobilization N pathways and N inputs is demonstrated by Komatsuzaki et al. (2015). In this unique BA immobilization approach, the N efficiencies (n = 36) were calculated based on a common N input, fall soil residual N + 80 kg N. The numerator reflects the difference in N immobilization (ΔNI) measured in spring above-ground biomass grown on two different soil treatments: fall soil residual N without additional N and fall soil residual N + 80 kg N.

Table 3.2. The cover crop N efficiency formulae used in **before-after experiments** are based on BMP efficiency equation 1, $E_{BMP} = (I_{(t+1)}/A_t) * 100$ %, and a variation of equation 2, $E_{BMP} = 1 - (L_{BMP}/L_C) * 100$ %. Abbreviations: "Sample after cover crop planting" represents the N measurements after cover crop growth, "Time (t+1)" means the time after cover crop growth, "Sample before cover crop planting" represents the N measurements taken before cover crop growth, "Time (t)" denotes the time before cover crop growth, "Unit" represents the reported N form and unit, "Method" indicates the experimental approach where "E" means empirical research and N efficiency calculation methods where "R" represents N efficiencies reported in the reference, "A" represents efficiencies calculated using the formulae in the table by the reference, and "N" represents efficiencies calculated using the formulae in the table with data supplied in the published paper reference; "Paper reference" means the study that the formulae were applied.

Before-and-after experiments		**Equation 1:** $E_{BMP} = \left(\frac{I_{(t+1)}}{A_t}\right) \times 100$ %				
		Numerator (N pathway)		**Denominator (N Input)**		
Method	**Paper reference**	**Sample after cover crop growth**	**Time (t+1)**	**Sample before cover crop growth**	**Time (t)**	**Unit**
E, A E, N E, N E, N, R E, N E, N	Shipley et al. 1992 Rannells et al. 1997 Ritter et al. 1998 Staver et al. 1998 Sainju et al. 2005 Clark et al. 2007	Above-ground **cover crop biomass** (Adjusted for below-ground biomass)	Mar, Apr, May Mar, Apr Apr Mar Apr Mar, May	Cash crop **fertilizer N**	Previous spring	kg TN ha^{-1} y^{-1}
E, N	Sainju et al. 2005	Above + below ground **cover crop biomass**	Apr	Cash crop **fertilizer N**	Previous spring	kg TN ha^{-1} y^{-1}
E, A E, N	Shipley et al. 1992 Clark et al. 2007	Above-ground **cover crop biomass** (Adjusted for below-ground biomass)	Mar Mar, May	**Soil residual N** Integrate (Int.) soil depth	Previous Sept, Oct Oct	kg TN ha^{-1} y^{-1}
E, A, R	Komatusaki et al. 2015	Difference between above-ground cover crop biomass **planted on soil residual N** and above-ground cover crop biomass **cultivated on soil residual N + 80 kg N**	Mar, Apr, May	**Soil residual N + 80 kg N** Int. soil depth	Previous Oct, Nov, Dec	kg TN ha^{-1} y^{-1}
E, N E, N	Rannells et al. 1997 Ritter et al. 1998	Above-ground **cover crop biomass** (Adjusted for below-ground biomass)	Dec Dec	Cash crop **fertilizer N**	Previous spring	kg TN ha^{-1} y^{-1}

Table 3.2 (continued). Cover crop N efficiency formulae used in before-and-after experiments.

Before-and-after experiments		**Equation 2:** $E_{BMP} = 1 - \left(\frac{L_{BMP)}}{L_C}\right) \times 100\%$				
		Numerator (N pathway)		**Denominator (N Input)**		
Method	**Paper reference**	**Sample after cover crop growth**	**Time (t+1)**	**Sample before cover crop growth**	**Time (t)**	**Unit**
E, N	Staver et al. 1998	**Groundwater export** Int. groundwater depth	Mar	**Groundwater export** Int. groundwater depth	Previous Sept, Oct	$\frac{mg\ NO_3\ L^{-1}\ y^{-1}}{Lysimeter}$
E, N	Rannells et al. 1997	**Soil N** Int. soil depth	Mar, Apr	**Soil residual N** Int. soil depth	Previous Oct	kg TN ha^{-1} soil y^{-1}
E, N	Rannells et al. 1997	**Soil N** Int. soil depth	Dec	**Soil residual N** Int. soil depth	Previous Oct	kg TN ha^{-1} soil y^{-1}
E, N	Coale et al. 2001	**Soil N** Int. soil depth	Apr, Jul	**Soil residual N** Int. soil depth	Previous Oct	mg NO_3 kg^{-1} soil y^{-1}

The BA experimental method also measured groundwater concentrations or export (mg NO_3 L^{-1} y^{-1}) and soil N inventories (kg TN ha^{-2} or mg NO_3 kg^{-1} y^{-1}) before and after cover crop growth. The BMP efficiency equation 2, $E_{BMP} = 1 - (L_{BMP}/L_C) * 100$ %, was applied to one groundwater study and three soil N inventory studies where the numerator represents the spring measurements of N content with cover crop growth and the divisor represents the previous fall N measurements without cover crop growth. Table 3.3 lists variations of equation 2 applied in empirical and modeled control (denominator: without cover crop) vs. treatment (numerator: with cover crop) experiments to measure the N flux in two direct pathway studies, two overland flow studies, three soil N inventory studies, and eight groundwater export studies.

Table 3.3. The cover crop N efficiency formulae used in **control-treatment experiments** were based on BMP efficiency equation 2, $E_{BMP} = 1 - (L_{BMP}/L_C) * 100$ %. Abbreviations: “Treatment/scenario with cover crop growth” represents the N measurements after cover crop growth, “Control plot/baseline without cover crop growth” represents the N measurements taken before cover crop growth, “Time” represents the time when samples were taken from a control/baseline and treatment/scenario, “Unit” represents the reported N form and unit, “Method” indicates the experimental approaches used in each study where “E” represents empirical research and “M” represents modeling research and the N efficiency calculation methods where “R” represents N efficiencies reported in the reference, “A” means efficiencies calculated using the formulae in the table by the reference, and “N” represents efficiencies calculated using the formulae in the table with data supplied in the published paper. “Paper reference” means the study that the formulae were applied.

Table 3.3. Cover crop N efficiency formulae used in control versus treatment experiments.

Control versus treatment experiments		**Equation 2:** $E_{BMP} = 1 - (\frac{L_{BMP}}{L_C}) \times 100\ \%$			
		Numerator (N pathway)	**Denominator (N input)**		
Method	**Paper reference**	**Treatment/scenario (w/cover crops)**	**Control plot/baseline (w/o cover crops)**	**Time**	**Unit**
		Direct pathways flux	**Direct pathways** flux		kg NO_3 ha^{-1} y^{-1}
M, N	Sadeghi et al. 2007			Apr	SWAT model
M, A, R	Yeo et al. 2014			Mar	SWAT model
E, R	Aryal et al. 2018	**Overland flow** flux	**Overland flow** flux	Apr	mg NO_3 L^{-1} y^{-1}
E, N	Smith et al. 2020			Mar	kg NO_3 ha^{-1} y^{-1}
M, N	Gaimaro et al. 2022	**Soil N** flux Integrate (Int.) soil depth	**Soil N** flux Int. soil depth	Dec	mg NO_3 L^{-1} soil y^{-1} HYDRUS 1-D model
E, N	Ritter et al. 1998	**Soil N** flux	**Soil N** flux	Apr	mg NO_3 kg^{-1} soil y^{-1}
E, N, R	Staver et al. 1998	Int. soil depth	Int. soil depth	Mar	kg NO_3 ha^{-1} y^{-1}
M, N	Gaimaro et al. 2022			Mar, May, Jun	mg NO_3 L^{-1} soil y^{-1} HYDRUS 1-D model
M, N	Gaimaro et al. 2022	**Groundwater N export** flux Int. groundwater depth	**Groundwater** N **export** flux Int. groundwater depth	Dec	kg NO_3 ha^{-1} y^{-1} HYDRUS 1-D model
		Groundwater N export flux	**Groundwater N export** flux		kg NO_3 ha^{-1} y^{-1}
E, N	Ritter et al. 1998	Int. groundwater depth	Int. groundwater depth	Apr	Monitoring well
M, A, R	Yeo et al. 2014			Mar	SWAT model
M, R	Lee et al. 2016			Mar	SWAT model
E, A, R	Fisher et al. 2018			May	Tile drain
M, R	Hively et al. 2020			Mar	SWAT model
M, N	Gaimaro et al. 2022			Mar, May, Jun	HYDRUS 1-D model
					mg NO_3 L^{-1} y^{-1}
E, N	Meisinger et al. 2017			May	Lysimeter
E, R	Sedghi et al. 2022			May	Lysimeter
					g NO_3 m^{-2} y^{-1}
E, N	Meisinger et al. 2017			May	Lysimeter

3.2.4 Adjustment for below-ground nitrogen accumulation

Most above-ground cover crop studies did not measure the N content of below-ground biomass, and this underestimates N efficiency based on immobilization since N in below-ground biomass is excluded. To avoid underestimating N efficiency in studies that measured N in the above-ground non-legume biomass, I adjusted the N measurement by a factor of 1.28 to include the estimated N captured by below-ground biomass. This factor is based on the average root N content published in the literature (Table 3.4). The Mann-Whitney rank sum test result detected no significant difference between the median N efficiency of above- and below-ground non-legume N immobilization reported by Sainju et al. (2005) (n = 3, Mdn = 31%. IQR = 23, 55) and adjusted N in above-ground biomass (n = 121, Mdn = 32, IQR = 19, 55). I did not adjust N measurements in cases where values were not clearly stated; instead, I reported the N efficiencies determined by the reference (Komatsuzaki et al. 2015). Shipley et al. (1992) provided the adjustment factor for their study to estimate N in above- and below-ground biomass. If references measured N in above- and below-ground <u>non-legume</u> and <u>legume</u> cover crops (Sainju et al. 2005), I used their measurements to calculate the N efficiency.

Table 3.4. Adjustment for below-ground nitrogen accumulation. The root adjustment factor, 1.28, is multiplied by the N measured in above-ground non-legume cover crops to estimate above- and below-ground N. This factor is based on the average percent, 22%, of total N (TN) concentration immobilized in root biomass. The remaining 78% represents the percent of TN concentration immobilized in the shoot and is used in the factor calculation, Factor = 100/Shoot N content. Abbreviation: “Paper reference” is the paper citation, “Cover crop” lists the species, “Root N content %” is the percent of TN concentration immobilized in below-ground biomass, “Shoot N content %” is the percent of TN concentration immobilized in above-ground biomass, “Factor calculation” shows the root adjustment factor calculation, and “Root adj. factor” represents the root adjustment factor.

Paper reference	**Cover crop**	**Root N content (%)**	**Shoot N content (%)**	**Factor calculation**	**Root adj. factor**
Siddique et al. (1990)	Wheat	20	80	= 100/80	1.28
Shipley et al. (1992)	Annual ryegrass	33	67	= 100/67	1.49
Shipley et al. (1992)	Cereal rye	25	75	= 100/75	1.33
Sainju et al. (2005)	Cereal rye (chisel-till)	19	81	= 100/81	1.23
Sainju et al. (2005)	Cereal Rye (no-till)	19	81	= 100/81	1.23
Sainju et al. (2005)	Cereal Rye (strip-till)	<u>13</u>	84	= 100/84	1.19
	Average root N %	**22**		**= 100/(100-22)**	**1.28**

3.2.5 Organization of selected cover crop literature

In addition to the experimental methods and N pathways that are the basis for cover crop N efficiency calculations (Tables 3.2 and 3.3), I identified six variables frequently appearing in the cover crop literature: research approach, temporal scale, study length, spatial scale, cover crop species, and soil characteristics that are defined in Table 3.5. For instance, I classified cover crop studies into empirical and modeling approaches, and N efficiencies were classified by temporal scales, publication year, data collection years, and growing days. The difference between publication year and data collection years is illustrated by a cover crop study published in 2015 by Komatsuzaki et al. The data, however, were collected between 2000-2002, and the calculated cover crop N efficiencies are assigned to the corresponding data collection year. I determined the number of growing days by the Julian day of the reported planting date and the sample date. I used the 15th as the default date when only a month was reported. The study length was classified as short-term (<4 years) or long-term (≥ 4 years), as defined by Liu et al. (2017b), due to the time needed to detect a water quality response after agricultural management changes. I also classified cover crop treatment areas into four spatial scales: plot- (< 0.25 ha), field- (0.5 – 20 ha), small watershed- (50 km^2), and large watershed scale (200 -300 km^2) (Vellidis et al. 2003; Baker et al. 2016; Lizotte et al. 2018; Hively et al. 2020). If the spatial scale was not defined, as in the case of Meisinger et al. (2017), I applied the plot scale defined by Sedghi et al. (2022), who conducted a similar groundwater leaching study at the same location. Empirical studies observed N efficiency in all cover crop plant species, including cover crop mix, which was classified as a legume if the mixture included legumes. Modeling studies limited experimental scenarios to non-legume cover crops. I reported the soil tillage type (Pickford 2022) stated in the paper reference.

Table 3.5. Organization of variables frequently appearing in the cover crop literature

Variable	**Classification**	**Description of Classes**
Cover crop species	Legumes	Crimson clover (*Trifolium incarnatum* L.)
		Hairy vetch (*Vicia villosa Roth*)
	Non-legumes	Annual ryegrass (*Lolium multiflorum Lam*.)
		Barley (*Hordeum vulgare L*.)
		Black oats (*Avena strigosa L*.)
		Cereal rye (*Secale cereale L*.)
		Forage radish (*Raphanus sativus*)
		Triticale (*Triticum secale L*.)
		Winter wheat (*Triticum aestivum L*.)
Experimental method	Before-after	N measurements normalized by previous spring cash crop fertilizer N or previous fall soil residual N defined as the soil N remaining after crop harvest.
	Control-treatment	A comparison of N between treatments with cover crop growth and controls without cover crop growth.
Research approach	Empirical	Observations and measurements influencing the N efficiency were measured directly by the researcher.
	Modeling	Data influencing N efficiency were drawn from sources not directly measured by the researcher.
N loss pathways	Biomass immobilization	The temporary storage of N in above- and below-ground cover crops.
	Direct pathways	Includes overland flow, lateral flow, and groundwater export
	Groundwater N export	The subsurface groundwater leachate in the vadose zone.
	Overland flow	The unconfined flow of water over the ground surface.
	Soil N inventory	Soil N is measured at depths ranging from 0 to 100 cm.
Soils	Hydric soils	Hydric soils were based on reported soil types in paper reference and the NRCS state hydric soils list (NRCS 2023).
	Hydrologic soil group: A, B, C, D, or any combination	Soil types provided by the paper reference were used to identify the hydrologic soil group. A = well-drained B = moderately well-drained C = moderately poorly drained D = poorly drained
	Tillage type: No-till Low-till Conservation till Average till	No-till: less than 15% crop residue after planting Low-till and reduced till: 15-29% crop residue after planting Conservation till: ≥30% crop residue after planting Average N efficiency is based on observations of cover crops on both no-till and conservation tillage
Spatial scale	Plot	≤ 0.25 hectare
	Field	0.5 – 20 hectares
	Sm. watershed	50 km^2
	Lg. watershed	200-300 km^2
Study length	Short-term	Consecutive years of cover crop growth < 4 years.
	Long-term	Consecutive years of cover crop growth ≥ 4 years.
Temporal scale	Data collection year	The calculated N efficiency is assigned to the year data were collected. If two or more years of data collection influenced the N efficiency, the last year of data collection is reported.
	Growing days	The number of growing days is the difference between the Julian day assigned to planting time and sampling time.
	Publication year	The year in which the study became publicly available.

3.2.6 Omitted cover crop nitrogen efficiencies

Applying N efficiency formulae to selected studies resulted in 10 cover crop P efficiencies based on two papers (Aryal et al. 2018; Smith et al. 2020) and 737 cover crop N efficiencies compiled from 18 papers. Due to the small sample size for P efficiencies, this literature review focused on cover crop N efficiencies. I limited the N efficiency dataset to percentage values greater than or equal to 1% and less than or equal to 100%. This removed 48 N efficiencies due to experimental errors or other unknown processes. In two cases, the low N efficiencies can be attributed to natural biological functions, where radish cover crops acted as a nitrogen sink during the growing season but, once killed by freezing soil in December, also served as a source of nutrients that provided subsequent N mineralization for the remainder of the winter (Gaimaro et al. 2022).

3.2.7 Data limitations

Inconsistencies among cover crop studies presented unique challenges in compiling a representative cover crop N efficiency dataset for the U.S. Coastal Plain Province. I reported the BMP efficiencies based on the original nitrogen form, NO_3-N or TN, to simplify the N efficiencies considered in this assessment. Reference the cover crop studies for the specific nutrient form such as dissolved, particulate, etc. This dataset is also limited to the common variables among the selected 18 cover crop studies. Thus, even though climate change has emerged as an important variable that could influence the water quality benefits of cover crops, particularly in the Chesapeake Bay watershed, climate change effects were not a recurring theme in the selected literature and are beyond the scope of this assessment (Wagena et al. 2018; Teodoro et al. 2020).

3.2.8 Statistical tests

I used SigmaPlot v 15 to conduct group comparisons, significance testing of two regressions, and create linear regression plots. To compare two groups, I conducted parametric t-tests and reported mean values. The Welch's t-test result was chosen if the Brown-Forsythe equal variance test failed. I selected the Student's t-test result if the equal variance test passed. Next, I applied the Holm-Sidak pairwise multiple comparison tests to mean group results. If normality tests failed the Shapiro-Wilk normality test ($p < 0.05$), I conducted a non-parametric Mann-Whitney Rank Sum test and used Dunn's Method for pairwise multiple comparisons. The median results are reported in Appendix B1-B6. I also conducted one-way ANOVA (analysis of variance) tests to compare three or more groups. I applied the Holm-Sidak pairwise multiple comparison procedures to compare mean values based on parametric one-way ANOVA tests. In cases where the normality test failed, I reported the median values from the non-parametric Kruskal-Wallis one-way ANOVA on ranks test and based my interpretation of the medians on the results of Dunn's Method, which I had applied to all subsequent pairwise multiple comparison procedures. To test the significance of two linear regression models and slopes, I used the R package lsmeans (Lenth 2016). I conducted one-way ANCOVA (analysis of covariance) using the Holm-Sidak method for pairwise comparisons of factors. The findings can be further verified by testing the trends using statistical tests accounting for autocorrelation in the time series.

I used R v 4.2.3 to bootstrap cover crop N efficiencies using the R package car (Fox et al. 2023). The data were resampled with replacement (i.e., bootstrapped) 5000 times, and 95% bootstrap confidence intervals were obtained for the regression coefficient in the linear regression models. I used R v 4.2.3 to create box plots using the R package ggplot2 (Wickham et al. 2023). The findings can be further verified by testing for independence of model residuals. The results of statistical tests were categorized as significant (S, $p < 0.05$), marginally significant (MS, $0.05 \leq p < 0.10$), or not significant (NS, $p \geq 0.10$).

3.3 Results

3.3.1 Agricultural BMP efficiency literature

In this section, I discuss widely varying agriculture BMP efficiencies at a global scale and agricultural BMPs at the scale of the U.S. Coastal Plain Province. An in-depth discussion on published cover crop N efficiency studies in the U.S. Coastal Plain Province follows. Overall, these cover crop studies can be described by similarities in spatial scale and soil characteristics.

<u>Wide-ranging agricultural management efficiencies</u>

A review of the agricultural BMP efficiencies found a BMP's N or P efficiency can vary widely (Harmel et al. 2004; Kay et al. 2009; Johnson et al. 2013; Liu et al. 2017b; Lizotte et al. 2018; Jain et al. 2019). For example, a comparison of country-scale BMP efficiencies showed wide N and P efficiency ranges for conservation tillage (N: 9 – 68%, P: 7-12%), cover crops (N: 15-96%), riparian buffers (N: 42-100%), and vegetative filter strips (N: 29-98%, P: 31-90%) (Table J2), and most BMP efficiencies remain <50% when multiple BMPs are applied (Arheimer et al. 2005a; Özcan et al. 2017; Engebretsen et al. 2019; Qiu et al. 2019). Within the U.S. Coastal Plain Province, Simpson et al. (2009) identified varying N and P efficiencies within the Chesapeake Bay watershed between agricultural BMPs and within the same classification of agricultural BMPs (Table J3). The wide range of efficiencies makes evaluating BMP impacts on water quality challenging to quantify and model. My initial review of the literature returned eleven different types of agricultural BMPs studied in the U.S. Coastal Plain Province (Table J4), and for this thesis chapter, I assessed cover crops to identify common variables that influence variable N efficiencies.

Coastal Plain province cover crop N efficiency studies

There is a long, well-documented history of cover crop N efficiency research in the U.S. Coastal Plain Province. The initial literature search attempted to compile studies published between 1980 – 2022, but the earliest cover crop study selected for this review was published in 1992 and continued to span three decades. Between 1992-2022, eighteen cover crop studies published sufficient data to identify 689 cover crop N efficiencies in my assessment (Table 3.6). The number of N efficiencies obtained from each study varied from 3 to 123, and the mean N efficiencies ranged widely from 16 to 79%. Except for five studies (Ranells et al. 1997; Sainju et al. 2005; Komatsuzaki et al. 2015; Aryal et al. 2018; Smith et al. 2020), the selected cover crop studies took place in the Embayed subregion within the Chesapeake Bay watershed.

Table 3.6. **Cover crop study N efficiency.** A summary of the mean cover crop N efficiency per cover crop study in the U.S. Coastal Plain Province published between 1980 – 2022. Abbreviations: “Reference ID” reflects the paper reference identification code consisting of the publishing year and the first three letters of the first author’s last name; “Paper reference” provides the citation, “n” denotes the sample size, “$\bar{x}$” lists the mean N efficiency as a percentage, “se” means the standard error, “sd” is the standard deviation, “Min” is the minimum, “Q1” means the first quartile, “Mdn” represents the median, “Q2” denotes the third quartile, and “Max” represents the maximum.

Reference ID	Paper reference	n	$\bar{x}$	se	sd	Min	Q1	Mdn	Q3	Max
1992SHI	Shipley et al. 1992	95	32	3	26	1	10	25	53	100
1997RAN	Ranells et al. 1997	108	43	3	29	1	11	47	71	89
1998RIT	Ritter et al. 1998	28	24	4	21	3	8	19	31	95
1998STA	Staver et al. 1998	45	38	5	31	1	15	28	70	96
2001COA	Coale et al. 2001	123	71	2	22	12	55	76	90	96
2005SAI	Sainju et al. 2005	14	57	6	24	23	31	64	75	89
2007CLA	Clark et al. 2007	42	38	4	28	3	15	29	54	97
2007SAD	Sadeghi et al. 2007	15	16	3	11	1	7	18	22	32
2014YEO	Yeo et al. 2014	18	53	5	21	25	38	52	65	93
2015KOM	Komatsuzaki et al. 2015	36	34	2	15	2	27	36	44	62
2016LEE	Lee et al. 2016	12	33	3	11	18	24	30	43	49
2017MEI	Meisinger et al. 2017	18	62	6	23	33	43	54	91	97
2018ARY	Aryal et al. 2018	3	62	13	22	45	49	54	70	86
2018FIS	Fisher et al. 2018	3	18	11	20	4	7	9	25	41
2020HIV	Hively et al. 2020	92	66	2	19	25	54	69	81	96
2020SMI	Smith et al. 2020	5	65	8	18	36	56	73	79	79
2022GAI	Gaimaro et al. 2022	28	79	4	22	21	69	86	97	100
2022SED	Sedghi et al. 2022	4	65	10	20	45	49	65	81	84

Figure 3.3 illustrates the wide variability of N efficiencies within the modeling and empirical studies. The publishing history of cover crop N efficiency studies indicates empirical methods were the preferred research method to test cover crop N efficiency until 2007. The earliest modeling cover crop study did not appear until 2007. Since then, concurrent published cover crop studies have included five modeling and seven empirical cover crop studies. Overall, empirical methods contributed 76%, and modeling methods contributed 24% of the cover crop N efficiencies evaluated in this assessment. These data demonstrate the need to understand why N efficiencies widely vary in the U.S. Coastal Plain Province. One of the goals of this assessment is to document the variables that influence the wide range of cover crop N efficiency reported in the empirical and modeling studies

I conducted a series of t-tests to compare mean efficiencies across publishing years and research methods (Table 3.7). The mean N efficiency of modeling and empirical studies published after 2006 ($n = 276$, 53% ± 2) was significantly greater than the mean N efficiency of empirical studies published before 2006 ($n = 413$, 47% ± 2) by a factor of 1.1 ($p = 0.01$). Results also showed the mean N efficiency of modeled studies published after 2006 ($n = 165$, 60% ± 2) was significantly greater than the mean N efficiency of empirical studies published after 2006 ($n = 111$, 43% ± 2) by a factor of 1.4 ($p < 0.001$) and all empirical N efficiencies ($n = 524$, 46% ± 1.3) by a factor of 1.3 ($p < 0.001$), as shown in Fig. 3.3. In contrast, empirical studies published before and after 2006 showed no significant differences.

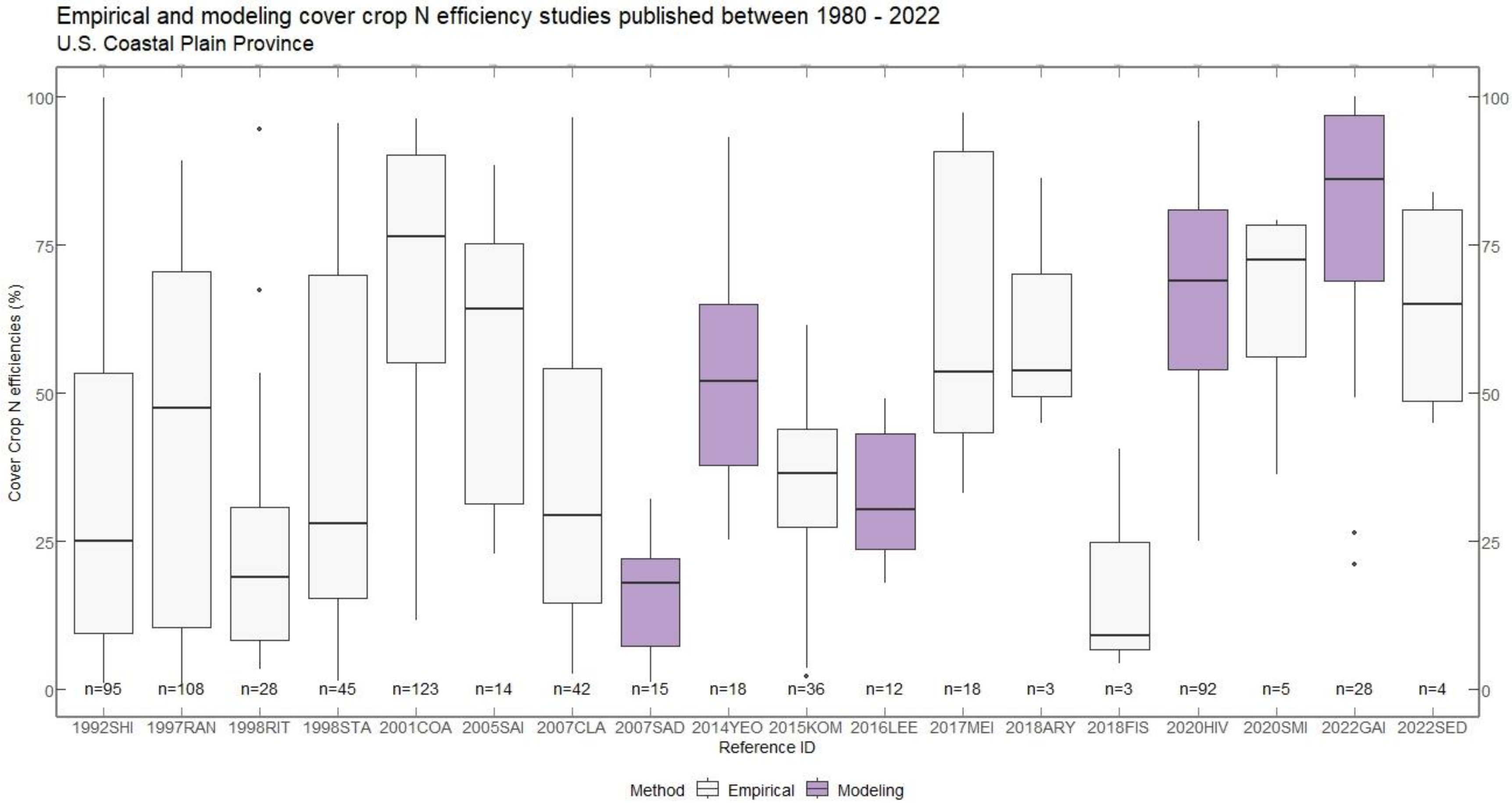


Figure 3.3. N efficiency distribution based on the publishing date. The boxplot displays the N efficiency distribution for each empirical and modeled study based on the publishing date. Most cover crop studies are based on empirical evidence; however, since 2007, modeled N efficiencies have made up nearly half of the published cover crop studies. Abbreviation: “Method” denotes empirical studies (white) and modeling (purple) studies, “Reference ID” represents the publishing year and first three letters of the primary author’s last name, and “n” indicates the number of N efficiencies per study.

Table 3.7. T-tests of N efficiency group means between published cover crop studies before and after 2006. Abbreviations: Approach: "E" represents empirical research, "M" represents modeling research, "Publishing year comparison" represents the published year of a cover crop study, "n" represents the sample size, "$\bar{x}$" represents the mean cover crop N efficiency as a percentage, "se" represents the standard error, "sd" represents the standard deviation, "min" represents the minimum N efficiency, "Q1" means the 25th percentile, "Mdn" represents the 50th percentile, "Q3" represents the 75th percentile, and "max" represents the maximum N efficiency, "Interpretation" represents the significance of the t-test, "t-test" describes the results of the two-tailed p-value (p), t-statistic (t), and corresponding degrees of freedom (df), and "Mann-Whitney" represents the Mann-Whitney Rank Sum Test p-value (p) for t-test comparisons failing the Shapiro-Wilk (p<0.05) normality test.

Approach	**Publishing year comparison**	**n**	**$\bar{x}$**	**se**	**sd**	**min**	**Q1**	**Mdn**	**Q3**	**max**
E	Before 2006	413	47	2	31	1	18	48	75	100
E + M	After 2006	276	53	2	27	1	32	51	77	100
E	After 2006	111	43	2	25	2	25	40	55	97
M	After 2006 (All years)	165	60	2	26	1	39	63	81	100
E	All years	524	46	1.3	30	1	19	45	74	100

Interpretation		**t-test**			**Mann-Whitney**
		P	**t**	**df**	**p**
E + M > E	After 2006 > Before 2006	0.011	-2.5	641	0.016
M > E	After 2006 > After 2006	<0.001	5.4	274	<0.001
E = E	Before 2006 = After 2006	0.119	-1.6	205	0.219
M > E	All years > All years	< 0.001	5.6	315	< 0.001

<u>Cover crop study characterization</u>

Cover crop studies were applied to four spatial scales: plot (< 0.25 ha), field (0.5-20 ha), small watershed (50 km^2), and large watershed (200-300 km^2). Empirical studies were applied to less than 20 ha croplands, and 69% of the cover crop N efficiencies were based on plot scale areas. The majority of cover crop N efficiencies were based on well-drained croplands less than 0.25 ha. Empirical studies have not yet been applied at a spatial scale greater than 50 km^2. In contrast, modeling studies applied cover crop scenarios to all spatial scales, but 82% of modeled N efficiencies are based on small or large-scale watersheds.

Additional t-tests of mean N efficiencies at the four spatial scales (Table 3.8) demonstrated that <u>modeled</u> large watershed scale is significantly greater (n = 104, 62% ± 2, p < 0.001) than the mean N efficiencies of the following spatial scales: empirical plot- (n = 473, 47% ± 1.4) and field-scale (n = 51, 41% ± 4.5) studies and modeled small watershed- (n = 21,

Table 3.8. **T-tests of N efficiency group means between four spatial scale**. Abbreviations: "App" denotes empirical "E" and modeling "M" approach, "Variable" lists the classes of variables, "Interpretation" states the significance of the t-test, "n" is the sample size, "t-test" represents the results of the two-tailed p-value (p), t-statistic (t), corresponding degrees of freedom (df), "$\bar{x}$" denotes the mean cover crop N efficiency expressed as a percent, "se" is the standard error, and "sd" is the standard deviation.

				t-test					
App	**Variable**	**Interpretation**	**n**	**p**	**t**	**df**	**$\bar{x}$**	**se**	**sd**
	A comparison of spatial scale								
E	Plot	Plot (E) = Field (E)	473	0.17	-1.39	522	47	1.4	29
	(< 0.25 ha)	Plot (E) > Sm. wshd (M)		< 0.001	5.2	25			
E	Field	Field (E) > Sm. wshd (M)	51	0.01	2.7	61	41	4.5	32
	(0.50-20 ha)								
M	Plot	Plot (M) > Plot (E)	28	< 0.001	7.4	33	79	4.1	22
M	Field	Field (M) = Field (E)	12	0.13	1.54	61	56	6.8	23
		Field (M) > Sm. wshd (M)		< 0.001	-4.2	31			
M	Sm. wshd		21				25	4.1	19
	(50 km^2)								
M	Lg. wshd	Lg. wshd (M) > Sm. wshd (M)	104	< 0.001	-7.6	123	62	2.0	21
	(200-300 km^2)	Lg. wshd (M) = Field (M)		0.36	0.9	114			
		Lg. wshd (M) > Plot (M)		< 0.0001	-3.9	130			
		Lg. wshd (M) > Field (E)		< 0.001	4.3	72			
		Lg. wshd (M) > Plot (E)		< 0.001	6.1	130			

25% ± 4.1) and plot-scale (n = 28, 79% ± 4.1, p < 0.0001). Mann-Whitney tests of median groups are available in Table K1. Additionally, the <u>modeled</u> plot-scale mean N efficiency (79% ± 4.1) is statistically greater than the mean N efficiency of the empirical plot-scale by a factor of 1.7 (47% ± 1.4, p < 0.001). In contrast, statistical tests revealed that the mean N efficiency of empirical plot- (p < 0.001) and field-scale studies (p = 0.01), and modeled field-scale- studies (n = 12, 56% ± 6.8, p < 0.001) are significantly greater than the mean N efficiency of <u>modeled</u> small watershed-scale. The t-tests indicate empirical field-scale studies are not significantly different from the N efficiencies of modeled field-scale or empirical plot-scales. The results are consistent with Table 3.7 results that empirical studies before and after 2006 were not statistically different. This result has important implications for modeling cover crop N efficiencies at plot, small watershed, and large watershed scales, demonstrating a need for modelers to reevaluate cover N efficiencies based on watershed scales and empirical research needs must include spatial scales larger than field scale to corroborate modeled N efficiencies.

Another common characteristic among the cover crop literature is the soil characterization of soils by tillage, hydric, and hydrological soil groups (HSG). The dominant soil characteristics influencing cover crop N efficiencies are no-tillage and well-drained soils. No-till soils applied to 75% of the cover crop studies, and 86% of modeled and empirical N efficiencies are based on moderately well-drained or well-drained soils. All empirical studies took place on moderately well-drained or well-drained soils. T-tests showed there is no significant difference between empirical no-till and low-till mean N efficiencies (Table 3.9). However, the empirical mean N efficiency of no-till soils ($n = 369$, 49% ± 1.6) and low-till soils ($n = 8$, 64% ± 7.5) were significantly greater than conventional till ($n = 38$, 38% ± 5, $p = 0.03$). In contrast, the mean N efficiencies of modeled no-till soils ($n = 150$, 64% ± 1.8) were significantly greater than empirical no-till soils (< 0.001). A comparison of empirical cover crop N efficiencies based on cropland hydric and non-hydric soils revealed no significant differences. However, the mean N efficiencies of modeled hydric soils ($n = 1520$, 64 ± 1.8) are significantly greater than empirical ($n = 312$, 45 ± 1.7, $p < 0.001$). Similarly, the mean N efficiencies of modeled moderately well-drained soils are significantly greater than empirical well and moderately drained soils and modeled poorly drained soils ($p < 0.001$). Mann-Whitney tests of median groups are available in Table K2. These results reflect significantly higher N efficiencies associated with modeled no-till, hydric soils, and moderately well-drained soils than empirical N efficiencies and the need for more empirical research on no-till and low-till croplands.

Table 3.9. **T-tests of N efficiency comparisons between hydric soils, tillage type, and hydrologic soils mean groups**. Abbreviations: "App" denotes empirical "E" and modeling "M" approaches, "Variable" lists the classes of variables, "Interpretation" states the significance of the t-test, "n" is the sample size, "t-test" represents the results of the two-tailed p-value (p), t-statistic (t), corresponding degrees of freedom (df), "$\overline{x}$" denotes the mean cover crop N efficiency expressed as a percent, "se" is the standard error, and "sd" is the standard deviation.

				t-test					
App	**Variable**	**Interpretation**	**n**	**p**	**t**	**df**	**$\overline{x}$**	**se**	**sd**
	A comparison of tillage type								
E	No-till (NT)	NT (E) > Conv (E)	369	0.03	2.2	405	49	1.6	31
		NT (E) = LT (E)		0.09	-1.9	7.6			
		NT (E) > Plow (E)		0.03	2.2	409			
E	Low-till (LT)	LT (E) > Conv (E)	8	0.03	-2.3	44	64	7.5	21
		LT (E) > Plow (E)		0.02	-2.5	48			
E	Conventional (Conv)	Conv (E) = Plow (E)	38	0.97	-0.04	78	38	5.0	31
E	Plowed seedbed (Plow)		42				38	4.3	28
E	Average tillage (NT, Conv)		10				34	7.7	25
M	NT	NT (M) > NT (E)	150	< 0.001	-6.3	374	64	1.8	22
	A comparison of hydric (Y) and non-hydric (N) soils								
E	Y - Hydric		312				45	1.7	30
E	N - Hydric	N - Hydric (E) = Y - Hydric (E)	212	0.235	1.2	522	48	2.0	29
M	Y - Hydric	Y - Hydric (M) > Y - Hydric (E)	150	< 0.001	6.9	460	64	1.8	22
		Y - Hydric (M) > N - Hydric (M)		< 0.001	-14.6	28			
M	N - Hydric		15				16	2.8	11
	A comparison of hydrologic soils group								
E	A	A (E) > A (M)	181	< 0.001	-8.3	32	44	2.0	27
E	B	B (E) > A (E)	260	0.014	2.4	439	51	1.9	31
E	AB		28				24	4.0	21
E	ABD		45				38	4.7	31
M	A		15				16	2.8	11
M	B	B (M) > AB (E)	28	< 0.001	9.6	54	79	4.1	22
		B (M) > ABD (E)		< 0.001	6	71			
		B (M) > B (E)		< 0.001	6.2	40			
		B (M) > A (M)		< 0.001	-10.5	41			
		B (M) > CD (M)		< 0.001	3.5	124			
M	AB		6				42	2.2	5
M	CD	CD (M) > A (M)	98	< 0.001	13.6	34	63	2.1	21
		CD (M) > AB (M)		< 0.001	6.8	17			

Summary of agricultural BMP efficiency literature

The agricultural BMP efficiency literature revealed widely varying N and P efficiencies at the country scale and smaller geographic scales, such as the Chesapeake Bay watershed. An in-depth review of eighteen cover crop studies in the U.S. Coastal Plain Province resulted in N efficiencies ranging from 18 ± 11 to 79 ± 4 (Table 3.6), and t-tests showed N efficiencies from modeling studies are significantly higher than empirical cover crop studies (Table 3.7). No significant differences were detected between N efficiencies from empirical studies published before 2006 or after 2006.

Most cover crop N efficiencies were based on well-drained croplands less than 0.25 ha (Table 3.9). The N efficiency data revealed empirical studies have not yet been applied at a spatial scale greater than 50 km^2 (Table 3.8). T-tests have important implications for modeling cover crop N efficiencies at plot, small watershed, and large watershed scales, demonstrating a need for modelers to reevaluate cover crop N efficiencies based on watershed scales and empirical research must include spatial scales larger than field scale to corroborate modeled N efficiencies. No-till and well-drained soils are dominant soil characteristics influencing cover crop N efficiencies. These results reflect significantly higher N efficiencies associated with modeled no-till, hydric soils, and moderately well-drained soils than empirical N efficiencies and the need for more empirical research on no-till and low-till croplands.

3.3.2 The basis of N efficiencies

This section presents the variations of equations 1 and 2 used in empirical and modeling experimental methods. The N pathways and N inputs in before-and-after (BA) and control versus treatment (CT) experiments for each cover crop study are summarized in Tables 3.10 and 3.11.

Table 3.10 shows the significance levels of combinations of modeling and empirical BA and CT experiments, and the significance level of mean group comparisons within BA and CT N pathways and BA immobilization types are provided in Tables 3.13, 3.14, and 3.15. Important patterns emerged in a summary table of ranked means and corresponding parameters, approach, methods, N pathway, and N input (Table 3.16).

N efficiency experimental methods: Before and After and Control versus Treatment

In this assessment of 18 cover crop studies in the U.S. Coastal Plain Province, I found empirical and modeling studies applied two types of experiments, sequential before-and-after (BA) and parallel control versus treatment (CT), to estimate N efficiency. The summary of cover crop N efficiencies in Tables 3.10 and 3.11 were based on empirical BA experiments (Shipley et al. 1992; Staver et al. 1998; Komatsuzaki et al. 2015), empirical CT experiments (Aryal et al. 2018; Fisher et al. 2018; Sedghi et al. 2022), and CT modeling scenarios (Yeo et al. 2014; Lee et al. 2016; Hively et al. 2020). Empirical BA experiments resulted in N efficiencies ranging from 7-71% (Table 3.10), and CT experiments used in empirical and modeling studies widely range from 16-86% (Table 3.11).

Multiple N pathways and N inputs were observed in BA and CT experiments. The BA biomass immobilization field experiments were the preferred N pathway to test cover crop N efficiency through 2006 (Table 3.10). Next most common were BA groundwater N export and soil N inventory experiments (Ranells et al. 1997; Staver et al. 1998; Coale et al. 2001) and empirical CT experimental methods observing soil N inventory or groundwater N flux (Ritter et al. 1998; Staver et al. 1998) in the early years of cover crop research before 2006 (Tables 3.10 and 3.11). The common N inputs used in empirical BA biomass immobilization studies were previous spring cash crop fertilizer N or previous fall soil residual N. In empirical BA groundwater N export and soil N inventory studies, the N content was normalized by the N inputs of the previous fall groundwater N export or the previous fall soil residual N.

Since 2007, however, observational field-based research methods transitioned away from BA immobilization studies to CT experiments observing N loss pathways such as direct pathways (overland flow, lateral flow, and groundwater export), groundwater N export, overland flow, and soil N inventories, and modeling cover crops studies followed suit. The CT experiments normalized N measured in N pathways with cover crop growth (direct pathway, overland flow, soil N, or groundwater N) by N inputs consisting of the N pathway without cover crops. This history of published cover crop studies illustrates a transition from empirical BA immobilization studies to primarily empirical or modeling CT groundwater N export studies since 2014.

Table 3.10. **Before-and-after experimental method.** The cover crop N efficiencies are based on empirical studies comparing N measurements before and after cover crop growth using equation 1, $E_{BMP} = (I_{(t+1)}/A_t) * 100$ %, and a variation of equation 2, $E_{BMP} = 1 – (L_{BMP(t+1)}/L_t) * 100$ % as a basis. Abbreviations: Approach: “E” represents empirical, “R” represents N efficiencies reported in the reference, “A” represents efficiencies calculated using the formulae in the table by the reference, and “N” represents efficiencies computed using the formulae in the table with data supplied in the published paper; “Paper reference” denotes the source of data used to calculate N efficiencies, “$\overline{x}$” represents the mean cover crop N efficiency as a percentage, “se” represents the standard error, “sd” denotes the standard deviation, “min” represents the minimum N efficiency, “Q1” means the 25th percentile, “Mdn” represents the median or 50th percentile, “Q3” represents the 75th percentile, and “max” represents the maximum N efficiency. The N efficiency of below-ground biomass was adjusted for empirical studies that measured above-ground non-legume cover crop N immobilization unless the N efficiency was stated in the paper reference.

Table 3.11. **Control versus treatment experimental method.** The cover crop N efficiencies are based on empirical and modeling studies that compared N measurements from a treatment (with cover crop growth) to a control (without cover crop growth) using equation 2, $E_{BMP} = 1 – (L_{BMP(t)}/L_t) * 100$ % as a basis. Abbreviations: Approach: “E” represents empirical research, “M” represents modeling research, “R” represents N efficiencies reported in the reference, “A” represents efficiencies calculated using the formulae in the table by the reference, and “N” represents efficiencies calculated using the formulae in the table with data supplied in the published paper; “Paper reference” denotes the source of data used to estimate N efficiencies, “n” represents the sample size, “$\overline{x}$” represents the mean cover crop N efficiency as a percentage, “se” represents the standard error, “sd” represents the standard deviation, “min” represents the minimum N efficiency, “Q1” represents the 25th percentile, “Mdn” represents the median or 50th percentile, “Q3” means the 75th percentile, and “max” represents the maximum N efficiency.

Table 3.10. **Before-and-after experimental method.** The cover crop N efficiencies (%) are based on empirical studies comparing N measurements before and after cover crop growth.

Approach	Paper reference	n	$\bar{x}$	se	sd	min	Q1	Mdn	Q3	max
Biomass immobilization experiments										
$E_{BMP} = \frac{\text{Sp. above ground biomass}}{\text{Prev. Sp. cash crop fertilizer N}} \times 100\ \%$										
E	Summary statistics	147	31	2	24	1	10	25	46	95
E, A	Shipley et al. 1992	48	27	3	24	1	8	22	39	72
E, N	Ranells et al. 1997	37	32	4	25	1	9	25	48	89
E, N	Ritter et al. 1998	9	31	10	31	4	12	18	36	95
E, N, R	Staver et al. 1998	19	31	3	13	13	21	28	39	70
E, N	Sainju et al. 2005	9	61	8	24	30	32	71	77	89
E, N	Clark et al. 2007	25	29	5	23	3	11	27	37	92
$E_{BMP} = \frac{\text{Sp. above+below ground biomass}}{\text{Prev. Sp. cash crop fertilizer N}} \times 100\ \%$										
E, N	Sainju et al. 2005	5	51	10	23	23	31	55	69	76
$N\ \% = \frac{\text{Sp. above ground biomass}}{\text{Prev. Fall soil residual N}} \times 100\ \%$										
E	Summary statistics	64	40	4	28	4	15	37	57	100
E, A	Shipley et al. 1992	47	36	4	27	4	13	36	53	100
E, N	Clark et al. 2007	17	51	7	30	8	25	52	77	97
$E_{BMP} = \frac{\text{Dec. above ground biomass}}{\text{Prev. Sp.cash crop fertilizer N}} \times 100\ \%$										
E	Summary statistics	24	8	1	6	1	4	7	10	24
E, N	Ranells et al. 1997	18	7	1	6	1	4	6	8	24
E, N	Ritter et al. 1998	6	10	2	6	3	7	9	11	20
$E_{BMP} = \frac{\text{Sp. above ground biomass: soil resid N+80 kg} - \text{above ground biomass: soil residual N}}{\text{Prev. Fall soil residual N+80 kg N}} \times 100$										
E, A, R	Komatsuzaki et al. 2015	36	34	2	15	2	27	36	44	62
Groundwater export experiments										
$E_{BMP} = 1 - \frac{\text{Sp. groundwater N export}}{\text{Prev. Fall groundwater N export}} \times 100\ \%$										
E, N, R	Staver et al. 1998	14	10	3	10	1	2	5	15	31
Soil N inventory experiments										
$E_{BMP} = 1 - \frac{\text{Sp. soil N}}{\text{Prev. Fall soil residual N}} \times 100\ \%$										
E	Summary statistics	163	69	2	22	4	56	75	86	96
E, N	Ranells et al. 1997	40	65	3	19	4	57	69	79	89
E, N	Coale et al. 2001	123	71	2	22	12	55	76	90	96
$E_{BMP} = 1 - \frac{\text{Dec. soil N}}{\text{Prev. Fall soil residual N}} \times 100\ \%$										
E, N	Ranells et al. 1997	13	58	5	18	20	46	63	72	86

Table 3.11. **Control versus treatment experimental method.** The N efficiencies (%) are based on empirical and modeling studies comparing N levels from a control (without cover crop) and treatment (with cover crop).

Approach	Paper reference	n	$\bar{x}$	se	sd	min	Q1	Mdn	Q3	max
Direct pathways experiments										
$E_{BMP} = 1 - \frac{\text{Sp. direct pathways N flux w/CC scenario}}{\text{Baseline.Sp. direct pathways N flux w/o CC}} \times 100\ \%$										
M	Summary statistics	21	26	5	22	1	10	21	32	80
M, N	Sadeghi et al. 2007	15	16	3	11	1	7	18	22	32
M, A, R	Yeo et al. 2014	6	52	9	22	25	38	50	69	80
Overland flow experiments										
$E_{BMP} = 1 - \frac{\text{Sp. overland flow N flux w/ CC}}{\text{Sp. overland flow N flux w/o CC}} \times 100\ \%$										
E	Summary statistics	8	63	6	18	36	52	64	79	86
E, R	Aryal et al. 2018	3	62	13	22	45	49	54	70	86
E, N	Smith et al. 2020	5	65	8	18	36	56	73	79	79
Soil N inventory experiments										
$E_{BMP} = 1 - \frac{\text{Dec. soil N flux w/CC scenario}}{\text{Baseline.Dec soil N flux w/o CC}} \times 100\ \%$										
M, N	Gaimaro et al. 2022	3	55	19	32	21	39	57	71	86
$E_{BMP} = 1 - \frac{\text{Sp. soil N flux w/CC scenario}}{\text{Baseline.Sp. soil N flux w/o CC}} \times 100\ \%$										
M, N	Gaimaro et al. 2022	11	86	5	16	51	76	97	99	100
$E_{BMP} = 1 - \frac{\text{Sp. soil N flux w/CC}}{\text{Sp. soil N flux w/o CC}} \times 100\ \%$										
E	Summary statistics	22	59	7	31	7	30	72	85	96
E, N	Ritter et al. 1998	10	28	5	15	7	20	27	39	53
E, N, R	Staver et al. 1998	12	85	2	8	69	80	85	93	96
Groundwater export experiments										
$E_{BMP} = 1 - \frac{\text{Dec. groundwater N flux w/CC scenario}}{\text{Baseline.Dec groundwater N flux w/o CC}} \times 100\ \%$										
M, N	Gaimaro et al. 2022	3	66	11	19	49	56	63	75	87
$E_{BMP} = 1 - \frac{\text{Sp. groundwater N flux w/CC scenario}}{\text{Baseline.Sp. groundwater N flux w/o CC}} \times 100\ \%$										
M	Summary statistics	127	63	2	22	18	46	65	81	100
M, A, R	Yeo et al. 2014	12	54	6	21	26	38	56	61	93
M, R	Lee et al. 2016	12	33	3	11	18	24	30	43	49
M, N	Gaimaro et al. 2022	11	82	6	21	26	80	89	93	100
M, R	Hively et al. 2020	92	66	2	19	25	54	69	81	96
$E_{BMP} = 1 - \frac{\text{Sp. groundwater N flux w/CC}}{\text{Sp. groundwater N flux w/o CC}} \times 100\ \%$										
E	Summary statistics	28	53	5	28	4	40	49	81	97
E, N	Ritter et al. 1998	3	17	7	13	6	10	14	22	31
E, N	Meisinger et al. 2017	18	62	23	6	33	43	54	91	97
E, A, R	Fisher et al. 2018	3	18	11	20	4	7	9	25	41
E, R	Sedghi et al. 2022	4	65	10	20	45	49	65	81	84

T-test comparisons: Multiple N pathways and N inputs influence empirical and modeled before and after and control versus treatment experiments

Multiple N pathways and N inputs observed in BA and CT experiments appear to have influenced cover crop N efficiency estimates. Therefore, I attempted to identify significant N pathways and N inputs in the data (Table 3.12). The t-test comparisons of mean N efficiencies based on empirical BA experiments revealed that N efficiencies referencing the N inputs (denominator) previous fall soil residual N and groundwater export (n = 290, 55% ± 1.7) were significantly greater than those using the previous spring fertilizer denominator (n = 176, 29% ± 1.8) by a factor of 1.9 (<0.001). This is important because 240 N efficiencies were based on the empirical BA N input of the previous spring fertilizer, and 212 N efficiencies were based on the previous fall soil residual N.

Additional t-test comparisons of N efficiencies based on empirical BA experiments also detected significant differences between three types of N pathways (numerators) normalized by the previous fall soil residual N. The numerator spring soil N inventory resulted in a mean efficiency (n = 163, 69% ± 1.7) significantly greater than the biomass N immobilization mean N efficiency (n = 100, 38% ± 2.4) by a factor of 1.8 ($p < 0.001$). The t-test also showed that the mean N efficiency of spring soil N inventory is marginally greater than that of December soil N (n = 13, p = 0.07, 58% ± 5.1). These results of empirical BA studies indicate measuring the N content of spring soil N inventory normalized by the previous fall soil residual N is likely to be higher than N efficiencies based on N pathways December soil N inventories or spring N immobilization.

Table 3.12. T-tests of N efficiency group means between before-after and control-treatment variables. Abbreviations: “App” represents empirical (E) and modeling (M) approaches, “Group comparison” represents the N efficiency formulae group, “Interpretation” represents the significance of the t-test, “n” represents the sample size, “t-test” represents the results of the two-tailed p-value (p), t-statistic (t), corresponding degrees of freedom (df), “$\bar{x}$” represents the mean cover crop N efficiency (%), “se” represents the standard error (%), and “sd” represents the standard deviation (%).

				t-test					
App	**Group comparison**	**Interpretation**	**n**	**p**	**t**	**df**	**$\bar{x}$**	**se**	**sd**
	Before-after (BA) formulae comparison of N inputs								
E	Prev spring (Sp) fertilizer	Prev fall > Prev Sp	176	<0.001	-10.7	411	29	1.8	24
E	Pre fall soil N and groundwater		290				55	1.7	28
	BA Immobilization formulae comparison of N inputs								
E	Prev Sp fertilizer	Prev fall > Prev Sp	176	0.002	3.13	274	29	1.8	24
E	Prev fall soil N		100				38	2.4	24
	BA N pathway normalized by previous fall soil N								
E	Spring Soil N inv.		163				69	1.7	22
E	Sp Immobilization (I)	Spring Soil N > I	100	<0.001	-10.8	261	38	2.4	24
E	December Soil N	Sp Soil N > Dec	13	0.07	1.8	174	58	5.1	18
	Control-treatment (CT) Formulae Comparison								
E	Soil N inventory (inv.)		22				59	6.6	31
M	Soil N inventory	Soil (M) > Soil (E)	14	0.04	-2.13	34	80	6.3	24
E	Groundwater (Gw)		28				53	5.3	28
M	Gw	Gw (M) > Gw (E)	130	0.03	2.13	156	63	1.9	21
	All BA vs All CT								
E	Before – After (BA)		466				45	1.4	30
E+M	Control – Treatment (CT)	CT > BA	223	<0.001	-6.2	490	59	1.8	26
	Groundwater export (E vs E + M)								
E	Gw (BA)		14				10	2.7	10
E+M	Gw (CT)	Gw (CT) > Gw (BA)	158	<0.001	-16	27	61	1.8	23
	Groundwater export (E vs E)								
E	Gw (BA)		14				10	2.7	10
E	Gw (CT)	Gw (CT) > Gw (BA)	28	<0.001	-7.3	38	53	5	28

A comparison of N efficiencies from soil N and groundwater N export CT experiments used in empirical and model studies showed that modeled soil N inventory was significantly greater ($n = 14$, 80% ± 6.3) than empirical soil N ($n= 22$, $p = 0.04$, 59% ± 6.6). Similarly, the mean N efficiency of modeled groundwater N export is significantly greater ($n = 130$, 63% ± 1.9) than the empirical groundwater N export ($n = 28$, $p = 0.03$, 53% ± 5.3). Overall, t-tests revealed that the mean N efficiency of modeled + empirical CT methods was significantly greater ($n = 223$, 59% ± 1.8) than the mean N efficiency of empirical BA experiments ($n = 466$, 45% ± 1.4) by a factor of 1.3 ($p < 0.001$).

Since 2014, more empirical and modeling studies observed N in CT groundwater N export experiments, and the t-tests indicated much higher mean N efficiencies ($n = 158$, 61% ± 1.8) than the empirical BA groundwater N export normalized by the previous fall groundwater N export ($n = 14$, 10% ± 2.78) by a factor of 6.1 ($p < 0.001$). Among empirical studies that observed groundwater N export, a t-test comparison of the BA and CT groundwater N export experiments resulted in a much greater mean N efficiency of empirical CT groundwater N export ($n = 28$, 53% ± 5) than empirical BA groundwater N normalized by the previous fall groundwater N export ($n = 14$, 10% ± 2.78) by a factor of **5.3** ($p < 0.001$). These statistical mean group comparison tests demonstrate that co-occurring CT experiments resulted in significantly higher cover crop N efficiencies than BA experiments normalized by the previous fall groundwater-based estimates. To review Mann-Whitney tests of median N efficiencies, review Table K3.

Kruskal-Wallis comparisons: before and after and control versus treatment N pathways

To understand the influence of N pathways commonly observed in BA and CT experiments, I conducted Kruskal-Wallis one-way ANOVA on ranks tests on BA N pathways (Table 3.13), BA immobilization types (Table 3.14), and CT N pathways (Table 3.15). The t-test results shown in Table 3.13 revealed soil N inventories had significantly greater median N efficiencies (n = 176, Mdn = 73%, IQR = 54-86) than groundwater N export (n = 14, Mdn = 5%, IQR = 2-16) by a large factor of 14.6 ($p < 0.001$). In addition, the mean N efficiencies displayed by soil N were significantly greater than biomass N immobilization (n = 276, Mdn = 28%, IQR = 10-48) by a factor of 2.6 ($p < 0.001$). The Kruskal-Wallis test results provide additional support for higher N efficiencies via soil N inventory rather than N immobilization.

Table 3.13. Presultsarametric (one-way ANOVA) and non-parametric (Kruskal-Wallis) tests of N efficiency groups based on before-after N pathway experiments. Abbreviations: "App" represents empirical (E) or modeling (M) approach, "Comparison" denotes the group name, "Interpretation" represents the significance of the ANOVA test, "n" represents the sample size, "$\overline{x}$" represents the mean cover crop N efficiency, "se" represents the standard error, "sd" represents the standard deviation, "Mdn" represents the 50th percentile, "LQ" means the 25th percentile, and "UQ" represents the 75th percentile, Holm-Sidak represents the parametric pairwise multiple comparison test results: p-value (p), t-statistic (t), corresponding degrees of freedom (df), and "Dunn's Method" represents the non-parametric pairwise multiple comparison test results: p-value (p) and Q-statistic (Q).

Before-after N pathway experiments			**One-way ANOVA**			**Kruskal-Wallis**		
App	**Comparison: N pathway**	**n**	**$\overline{x}$**	**se**	**sd**	**Mdn**	**LQ**	**UQ**
E	Biomass N immobilization	276	32	1.5	25	28	10	48
E	Groundwater (GW) N export	14	10	2.7	10	5	2	16
E	Soil N inventory	176	68	1.6	21	73	54	86
	Pairwise Multiple Comparison Procedure:		**Holm-Sidak**			**Dunn's Method**		
App	**Interpretation**		**p**	**t**	**df**	**p**	**Q**	
E	Soil N > GW		<0.001	9.1	2	<0.001	7.4	
E	Soil N > Immobilization		<0.001	16.2		<0.001	12.5	
E	Immobilization > GW		<0.001	3.5		0.006	3.1	

Empirical BA immobilization experiments observed spring above-ground biomass, spring above + below-ground biomass, and December samples of above-ground biomass (Table 3.14). These N immobilization types were normalized by the N input from the previous spring cash crop fertilizer N, and tests showed that the mean N efficiency of both spring above + below-ground biomass (n = 5, 51% ± 10) and the spring above-ground biomass (n = 147, 31% ± 2) were much greater than the December above-ground biomass (n = 24, 8% ± 6, $p < 0.001$). These comparisons indicate mean N efficiencies based on N immobilization in the spring above + below ground biomass or spring above-ground biomass is significantly greater than December above-ground biomass.

Table 3.14. Prarametric (one-way ANOVA) and non-parametric (Kruskal-Wallis) tests of N efficiency groups based on before-after N immobilization experiments. Abbreviations: "App" represents empirical (E) or modeling (M) approach, "Comparison" denotes the group name, "Interpretation" represents the significance of the ANOVA test, "n" represents the sample size, "$\overline{x}$" represents the mean cover crop N efficiency, "se" represents the standard error, "sd" represents the standard deviation, "Mdn" represents the 50th percentile, "LQ" means the 25th percentile, and "UQ" represents the 75th percentile, Holm-Sidak represents the parametric pairwise multiple comparison test results: p-value (p), t-statistic (t), corresponding degrees of freedom (df), and "Dunn's Method" represents the non-parametric pairwise multiple comparison test results: p-value (p) and Q-statistic (Q).

Before-after: Three immobilization types normalized previous spring cash crop fertilizer N								
			One-way ANOVA			**Kruskal-Wallis**		
App	**Compare Immobilization types**	**n**	**$\overline{x}$**	**se**	**sd**	**Mdn**	**LQ**	**UQ**
E	Spring (Sp) above ground (AG)	147	31	2	24	25	10	47
E	Sp above + below ground (ABG)	5	51	10	23	55	27	72
E	December AG	24	8	6	1	6.5	4	10
	Pairwise Multiple Comparison Procedure:		**Holm-Sidak**			**Dunn's Method**		
App	**Interpretation**		**p**	**t**	**df**	**p**	**Q**	
E	Sp ABG > December AG		<0.001	3.8	2	<0.001	3.9	
E	Sp ABG = Sp AG		0.06	3.8		0.26	1.7	
E	Sp AG > Dec AG		<0.001	4.7		<0.001	5.1	

The Kruskal-Wallis tests of the four N pathways observed in CT experiments (Table 3.15) indicate the median N efficiency of empirical and modeled CT soil N experiments (n = 36, Mdn = 77%, IQR = 43-93) was significantly greater than modeled direct pathways (n = 21, Mdn = 21%, IQR = 9-33) by a factor of 3.7 (p <0.001). In addition, empirical CT overland flow experiments (n = 8, Mdn = 64%, IQR = 47-79) and the empirical and modeled groundwater export (n = 158, Mdn = 62%, IQR = 43-81) were both significantly greater than the modeled direct pathways by a factor of ~3 (p = 0.017). The tests show N efficiencies are higher when observations are based on soil N inventories, overland flow, or groundwater export.

Table 3.15. rParametric (one-way ANOVA) and non-parametric (Kruskal-Wallis) tests of N efficiency groups based on control-treatment experiments. Abbreviations: "App" represents empirical (E) or modeling (M) approach, "Comparison" denotes the group name, "Interpretation" represents the significance of the ANOVA test, "n" represents the sample size, "$\overline{x}$" represents the mean cover crop N efficiency, "se" represents the standard error, "sd" represents the standard deviation, "Mdn" represents the 50th percentile, "LQ" means the 25th percentile, and "UQ" represents the 75th percentile, Holm-Sidak represents the parametric pairwise multiple comparison test results: p-value (p), t-statistic (t), corresponding degrees of freedom (df), and "Dunn's Method" represents the non-parametric pairwise multiple comparison test results: p-value (p) and Q-statistic (Q).

Control–treatment N pathway experiments			**One-way ANOVA**			**Kruskal-Wallis**		
App	**Comparison: N pathway**	**n**	**$\overline{x}$**	**se**	**sd**	**Mdn**	**LQ**	**UQ**
M	Direct pathways (DP)	21	26	4.8	21.9	21	9	33
E	Overland flow	8	63	6.4	18.1	64	47	79
E + M	Soil N inventories	36	67	5.0	29.7	77	43	93
E + M	Groundwater (GW) export	158	61	1.8	23.1	62	43	81

	Pairwise multiple comparison procedure:	**Holm-Sidak**			**Dunn's Method**	
App	**Interpretation**	**p**	**t**	**df**	**p**	**Q**
E + M > M	Soil N > DP	<0.001	6.17	3	<0.001	5.41
E > M	Overland flow > DP	<0.001	3.72		0.017	2.98
E + M > M	GW > DP	<0.001	6.27		<0.001	5.21

Summary of the basis of N efficiencies

Empirical BA experiments resulted in N efficiencies that widely range from 7-71% (Table 3.10), and control versus treatment (CT) experiments used in empirical and modeling studies widely range from 16-86% (Table 3.11). Since 2007, however, observational field-based research methods began to transition from before-and-after (BA) immobilization studies to CT experiments observing N loss pathways such as direct pathways (overland flow, lateral flow, and groundwater export), groundwater N export, overland flow, and soil N inventories, and modeling cover crops studies followed suit. This history of published cover crop studies indicates a preference for empirical or modeling CT groundwater N export experiments instead of empirical BA immobilization studies, which could introduce biased cover crop N efficiencies.

The basis of cover crop N efficiencies is explained by before-and-after and control versus treatment methods used in empirical and modeling studies observing combinations of N pathways normalized by N inputs (Table 3.16). For example, modeling CT methods that measure soil N flux (N pathway) normalized by the soil N flux without cover crops (N input) result in cover crop mean N efficiencies > 50% (reference dash line in Table 3.16). In contrast, empirical BA methods observing biomass N immobilization (N pathway) normalized by the previous spring cash crop fertilizer N or fall soil residual N (N input) resulted in N efficiencies < 50%. Empirical BA methods generally result in wide-ranging mean N efficiencies (10-80%). Tests indicate higher N efficiencies are associated with the following: model > empirical approach, CT > BA methods, and soil N > all other N pathways and N inputs ($p < 0.001$).

Table 3.16. Ranked mean ± se values of cover crop N efficiency (N Eff) reported in the scientific literature during 1982-2020 using combinations of approach, method, numerator, and denominator in equations 1 and 2. Significant combinations of variables are shown below the table. Abbreviations: $\bar{x}$ ± se = standard error of the mean, Emp = Empirical, CT = concurrent control vs. treatment, BA =sequential Before-and-After treatments, I = biomass N immobilization, Spr. Soil = spring soil N inventory (BA) or soil N flux with cover crops (CT), Dec soil = December soil N inventory with cover crops (BA), Spr. Gw = Spring groundwater N export (BA) or groundwater N flux with cover crops (CT), Prev Spr Fert = Previous spring cash crop fertilizer N, Soil N = Previous fall soil residual N (BA) or Soil N flux without cover crops (CT), Gw N export = Previous fall groundwater N (BA) or groundwater N flux without cover crops (CT). Dash line delineates N efficiencies greater than or less than 50%. Data source: Table 3.12. P-value sources: Tables 3.7, 3.12, 3.13.

	Model > Empirical $p < 0.001$		CT > BA $p < 0.001$		Spr soil > I > Spr Gw $p < 0.001$				Prev Fall soil > Prev Spr Fert $p < 0.001$		
N Eff	Approach		Method		N pathway (Numerator)				N input (Denominator)		
$\bar{x}$ ± se	Model	Emp	CT	BA	I	Spr Soil	Dec Soil	Spr Gw	Prev Spr Fert	Soil N	Gw N export
80 ± 6	x		x			x				x	
69 ± 2		x		x		x				x	
63 ± 2	x		x					x			x
61 ± 2	x	x	x					x			x
59 ± 2	x	x	x								
59 ± 7		x	x			x				x	
58 ± 5		x		x			x			x	
55 ± 2		x		x		x		x		x	x
53 ± 5	x		x					x			x
45 ± 1		x		x							
38 ± 2		x		x	x					x	
29 ± 2		x		x	x				x		
10 ± 3		x		x				x			x

3.3.3 The effect of temporal scale on cover crop N efficiencies

Figure 3.4 illustrates the effect of two temporal scales on the wide-ranging cover crop N efficiencies in the U.S. Coastal Plain Province. Yet, the data collection year stretches across 30 years from 1987 to 2018 (Fig. 3.4a, top panel) and has shown a significant positive association with N efficiencies ($r^2 = 0.15$, $p < 0.001$, 1.3% yr^{-1}). T-tests, summarized in Table 3.17, showed that the mean N efficiency of the years between 2008 and 2018 (n = 542, 46% ± 1.3) is significantly greater than before 2002 (n = 147, 65% ± 1.9) by a factor of 1.4 ($p < 0.001$) which agrees with results in Table 3.7. The results also show that the mean N efficiency of earlier

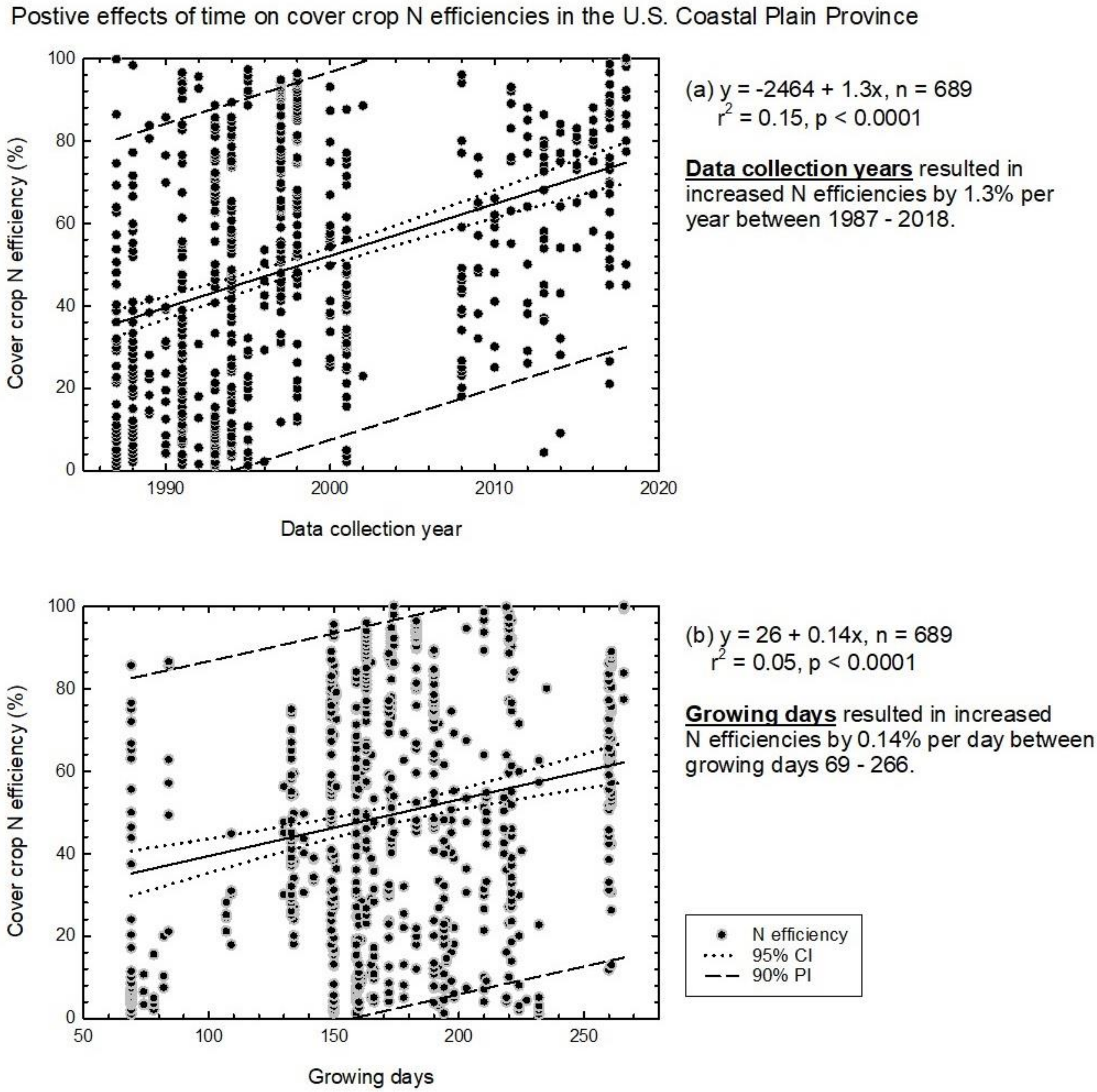


Figure 3.4. Data collection years (Fig. 3.4a) and growing days (Fig. 3.4b) have strong positive effects on cover crop N efficiencies and illustrate the wide range of cover crop N efficiencies reported in the literature. The association between N efficiencies and data collection year is statistically significant ($p < 0.0001$) with a 95% bootstrap CI [1.06, 1.45] for the regression coefficient, 1.3 (Fig. 3.4a, top). The association between N efficiencies and growing days is significant ($p < 0.0001$) with a 95% bootstrap CI [0.09, 0.18] for the regression coefficient, 0.14 (Fig. 3.4b, bottom). Confidence interval (CI) is the range where the regression line values, or slope, will fall 95% of the time for repeated measurements. Prediction interval (PI) is the range where the individual observation (y) will fall 90% of the time for repeated measures.

empirical studies is not statistically different from that of recent empirical studies. In Figure 3.4b, the effect of growing days has a significant positive increase ($r^2 = 0.05$, $p < 0.001$, 0.14% d^{-1}) on N efficiencies between growing days 69 to 266 or approximately 2 to 9 months of cover crop growth. The high number of growing days reflects cover crop planting in mid-October followed by sampling in July (Coale et al. 2001) or planting in mid-September followed by sampling in June (Gaimaro et al. 2022). Overall, data collection years and growing days have strong positive effects on cover crop N efficiencies. Mann-Whitney tests of median N efficiencies are available in Table K4. In the following two sections, I attempted to identify variables to explain the wide variability in N efficiencies across temporal scales.

Table 3.17. **T-test of data collection years**. Significance levels for t-test comparisons between groups of data collection years. Abbreviations: App: "E" represents empirical research, "M" represents modeling research, "Variable" represents the classes of variables, "Interpretation" represents the significance of the t-test, "n" represents the sample size, "t-test" describes the results of the two-tailed p-value (p), t-statistic (t), corresponding degrees of freedom (df), "$\bar{x}$" represents the mean cover crop N efficiency expressed as a percent, "se" represents the standard error, and "sd" represents the standard deviation.

				t-test					
App	**Variable**	**Interpretation**	**n**	**p**	**t**	**df**	**$\bar{x}$**	**se**	**sd**
	A comparison of data collection years								
E + M	Before 2006	After 2006 > Before 2006	542	< 0.001	-8.38	295	46	1.3	30
E + M	After 2006		147				65	1.9	23
E	Early E: 1987-2002	Early E = Recent E	509	0.274	1.1	522	46	1.3	30
E	Recent E: 2012-2018		15				55	6.7	26

3.3.4.The effects of data collection years on cover crop N efficiencies

In this section, I present significant relationships between the cover crop N efficiencies and data collection years to explain the wide variability depicted in Figure 3.4a. First, I present the significant relationships between years and N efficiencies based on empirical and modeling research approaches and before-and-after (BA) and control versus treatment (CT) experimental approaches (Fig. 3.5). Figure 3.6 depicts a comparison between the N inputs (denominator) of BA N efficiency formulae, previous spring fertilizer N (Fig. 3.6a), and previous fall soil residual N (Fig. 3.6b). Next, I present the effects of years on the N efficiencies computed modeled groundwater export and narrow N efficiencies to long-term modeling and empirical N efficiencies (Fig. 3.7). Figure 3.8 shows the overall effect of years on leguminous and non-leguminous N efficiencies. The significant relationships between data collection years and N efficiencies based on the N pathways and N inputs measured in empirical and modeled experiments are summarized in Table 3.18.

Table 3.18. Slope analysis of linear regression for data collection year and N efficiency. A summary of numerator and denominator variables used in cover crop N efficiency experimental approach during data collection years. Significant relationships are described by a linear regression and slope comparison interpretation. Abbreviation: “Fig.” represents the figure number, “Met” identifies the research approach, empirical (E) or modeling (M), and experimental methods before-after (BA) or control-treatment (CT), the “Numerator” lists the N with cover crop growth and the “Denominator” lists the N measurement without cover crop growth, “n” represents the sample size, “y-int” represents the y-intercept, “Slope” denotes the coefficient, “Interp (p)” references the figure that depicts slopes compared, interpretation of the slope comparison, and p-value, “r^2” represents the linear regression model r-squared value, “p” represents the p-value of the regression coefficient, and “Year” represents the range of data collection years.

	N efficiency formulae variables,									
Fig.	**Met**	**Numerator**	**Denominator**	**n**	**y-int**	**Slope**	**Interp (p)**	**r^2**	**p**	**Year**
	A comparison of **research methods**, Empirical vs. Modeling									
5a	E, BA, CT	All E-BA summary Sp. and Dec. biomass Sp. Groundwater (Gw) export Sp. and Dec. soil N	All E-BA summary Previous sp. fertilizer (fert) N Prev. fall Gw export Prev. fall soil residual (resid) N	524	-3050	1.6	5a ≠ 5c (0.04)	0.08	< 0.001	1987-2018
		All E-CT w/ CC: Sp. overland flow Sp. soil N inventory (inv) Sp. Gw export	All E-CT w/o CC: Sp. overland flow Sp. soil N inv Sp. Gw export							
5c	M, CT	All M-CT w/ CC: Sp. direct pathways (DP) Sp. and Dec. soil inv Sp. and Dec. Gw export	All M-CT w/o CC: Sp. DP Sp. and Dec. soil inv Sp. and Dec. Gw export	165	-4567	2.3		0.40	< 0.001	1995-2018
	A comparison of **experimental approaches**, before-after vs. control-treatment									
5b	E, BA	All E, BA summary	All BA summary	466	-4694	2.38	5b ≠ 5d (0.04)	0.12	< 0.001	1987-2002
5d	E + M, CT	All E + M-CT w/ CC	All E + M-CT w/o CC	223	-2058	1.05		0.14	<0.0001	1989-2018
	A comparison of **empirical BA denominators**: previous spring cash crop fertilizer N vs. previous fall soil residual N									
6a	E, BA	Sp. above-ground (gr) Sp. above + below-gr Dec. above-gr	Prev. sp. fert N	176	-3296	1.67	**6a = 6b**	0.06	0.0007	1987-2002
6b	E, BA	Sp. soil N Dec. soil N Dec. Gw export	Prev. fall soil resid N	290	-2764	1.41		0.05	0.0002	1987-2001

Table 3.18 (continued). Slope analysis of linear regression for data collection year and N efficiency.

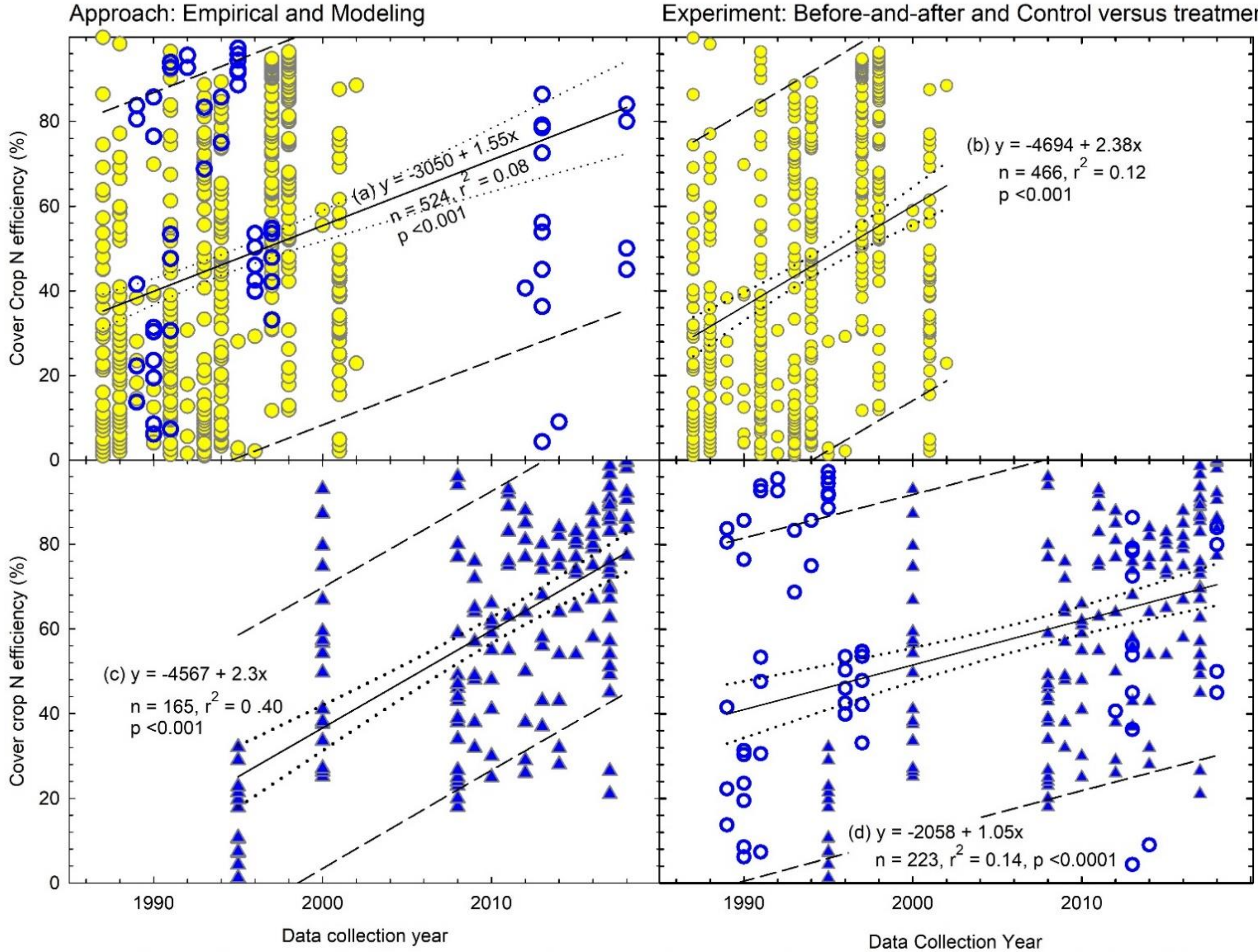
Fig.	Met	Numerator	Denominator	N	y-int	Slope	Interp (p)	r^2	p	Year
	N efficiency formulae variables									
	A comparison of **long-term groundwater export model and empirical immobilization experiment**									
7a	M, CT	Sp. Gw export w/ CC	Sp. Gw export w/o CC	130	-3576	1.8	n/a	0.17	<0.0001	2000-2018
7b	M, CT	Sp. Gw export w/ CC	Sp. Gw export w/o CC	92	-3563	1.8	7b ≠ 7c (0.04)	0.08	0.008	2008-2017
7c	E, BA	Sp. above-gr	Prev. sp. fert N	14	5827	-2.9		0.45	0.01	1988-1995
	Legume cover crop N efficiencies									
8a	E, BA, CT	Sp. above-gr Dec. above-gr Sp. Gw export w/ CC	Prev. sp. fert N Prev. fall soil resid N Sp. Gw export w/o CC	155	-5213	2.6	n/a	0.23	< 0.001	1987-2018
	Non-legume cover crop N efficiencies									
8c	E, BA, CT	Sp. above-gr biomass Dec. above-gr biomass Sp. Gw export w/ CC Sp. overland flow Sp. and Dec. soil N inv	Prev. sp. fert N Prev. fall soil resid N Sp. or Fall Gw export w/o CC Sp. overland flow Sp. soil N inv	369	1473	0.76	n/a	0.02	0.006	1987-2014

Positive effect of empirical and modeling approaches and BA and CT methods

Figure 3.5 depicts the effects of years on N efficiencies classified by research approach, empirical (Fig. 3.5a) or modeling (Fig. 3.5c), and experimental methods, BA (Fig. 3.5b) or CT (Fig. 3.5d). Empirical methods using BA and CT experiments ($r^2 = 0.08$, 1.6% yr^{-1}) and modeled CT experiments ($r^2 = 0.40$, 2.3% yr^{-1}) exhibited a significant positive increase ($p < 0.001$). The N efficiencies based on modeled CT experiments increased 1.5 times faster than empirical BA and CT ($p = 0.04$). The effect of years between 1987 and 2018 had a significant positive increase ($p < 0.001$) on the N efficiencies based on BA experimental methods ($r^2 = 0.12$, 2.38% yr^{-1}) and CT methods applied in empirical and modeling studies ($r^2 = 0.14$, 1.1% yr^{-1}). The N efficiencies based on BA empirical experiments increased 2.2 times faster over a narrower timeframe than those based on CT models ($p = 0.04$). These data show strong positive effects of data collection year on cover crop N efficiency based on empirical and modeling experimental methods between 1987-2018.

Figure 3.5. Empirical and modeling methods using before-and-after and control-treatment experimental methods are the basis of cover crop N efficiencies shown in the left column. Figure 3.5a (top left) displays N efficiencies based on empirical studies using both experimental approaches and Figure 3.5c (bottom left) shows N efficiencies based on modeling methods using control-treatment experiments. The cover crop N efficiency data are based on two experimental methods shown in the right column: before-after (Fig. 3.5b, top right) and control-treatment (Fig. 3.5d, bottom right) used in empirical and modeling studies. Confidence interval (CI) is the range where the regression line values, or slope, will fall 95% of the time for repeated measurements. Prediction interval (PI) is the range where the individual observation (y) will fall 90% of the time for repeated measures.

Effect of data collection year on cover crop N efficiencies (empirical and modeling methods)



The basis of N efficiency formulae is below.

<u>Before-after method</u>

$\mathbf{E_{BMP} = (I / A) * 100}$ %

I = spring or December N immobilization

A = <u>previous spring fertilizer N</u> or <u>prev. fall soil residual N</u> without cover crop growth

$\mathbf{E_{BMP} = 1 - (L_{BMP} / L) * 100}$ %

L_{BMP} = spring or December groundwater export or soil with cover crop growth

L = <u>previous fall soil residual N</u> or <u>prev. groundwater N export</u> without cover crop growth

<u>Control-treatment method</u>

$\mathbf{E_{BMP} = 1 - (L_{BMP} / L) * 100}$ %

L_{BMP} = spring or December N sampled in direct pathwyas, overland flow, groundwater export, or soil N inventories <u>with cover crop growth</u>

L = spring or December N sampled in direct pathways, overland flow, groundwater export, or soil N inventories <u>without cover crops</u>

<u>N efficiency</u>
- Empirical before-after
- Empirical control-treatment
- Modeling control-treatment
- 90% PI
- 95% CI

(a) <u>**Empirical before-after and control-treatment experiments**</u> increased N efficiencies by 1.55% y^{-1} between 1987 to 2018.
(c) <u>**Modeling control-treatment experiments**</u> increased N efficiencies by 2.3% y^{-1} between 1995 to 2018.

(b) <u>**Before-after experiments used in empirical studies**</u> increased N efficiencies by 2.38% y^{-1} between 1987 to 2002.
(d) <u>**Control-treatment experiments use in empirical and modeling studies**</u> increased N efficiency by 1.05% y^{-1} between 1989 - 2018.

Positive effect of empirical BA experimental methods

The effect of years on empirical BA experiments observing multiple N pathways (numerators) normalized by the previous spring cash crop fertilizer N (top panel) or the previous fall soil residual N (bottom panel) is illustrated in Figure 3.6. Years had a significant positive increase in N efficiencies based on the previous spring fertilizer N ($r^2 = 0.06$, $p = 0.0007$, 1.7%/y increase) and the previous fall soil residual N ($r^2 = 0.05$, $p = 0.0002$, 1.4% yr^{-1}) between 1987 and 2002. An equal slopes test conducted in ANCOVA detected no significant differences between slopes ($b = 1.5\%$ yr^{-1}, Table K7). A subsequent analysis of the equal slopes models revealed that the adjusted mean N efficiency of the fall soil residual N (Fig. 3.6b, adj. $\overline{x} = 53 \pm 1.6$, CI[50.2, 56.4]) is significantly greater than the adjusted mean of the previous spring fertilizer N (Fig. 3.6a, adj. $\overline{x} = 32 \pm 2.1$, CI[27.7, 35.8]) by a factor of 1.7 ($t = 6.8$, $p < 0.001$). These data revealed that N efficiencies based on the previous fall soil residual N and previous spring fertilizer N increased at the same rate; however, significantly higher mean N efficiencies are based on the previous fall soil residual N.

Contrast between long-term CT groundwater model and empirical immobilization studies

Figure 3.7 shows the long-term N efficiencies based on modeling groundwater N export and empirical N immobilization. Figure 3.7a (top panel) shows the majority of N efficiencies post-2000 are based on spring and December groundwater export models, and the effect of years has a significant positive increase ($r^2 = 0.17$, $p < 0.0001$, 1.8% yr^{-1}) on N efficiencies between 2000 and 2018. Many of these N efficiencies were reported by Hively et al. (2020), and the data display a significant positive increase ($r^2 = 0.08$, $p = 0.008$, 1.8% yr^{-1}) with ten consecutive years of rye, barley, and wheat cover crop growth and subsequent modeled CT groundwater N export scenarios (Fig. 3.7b). In contrast, Figure 3.7c shows a significant

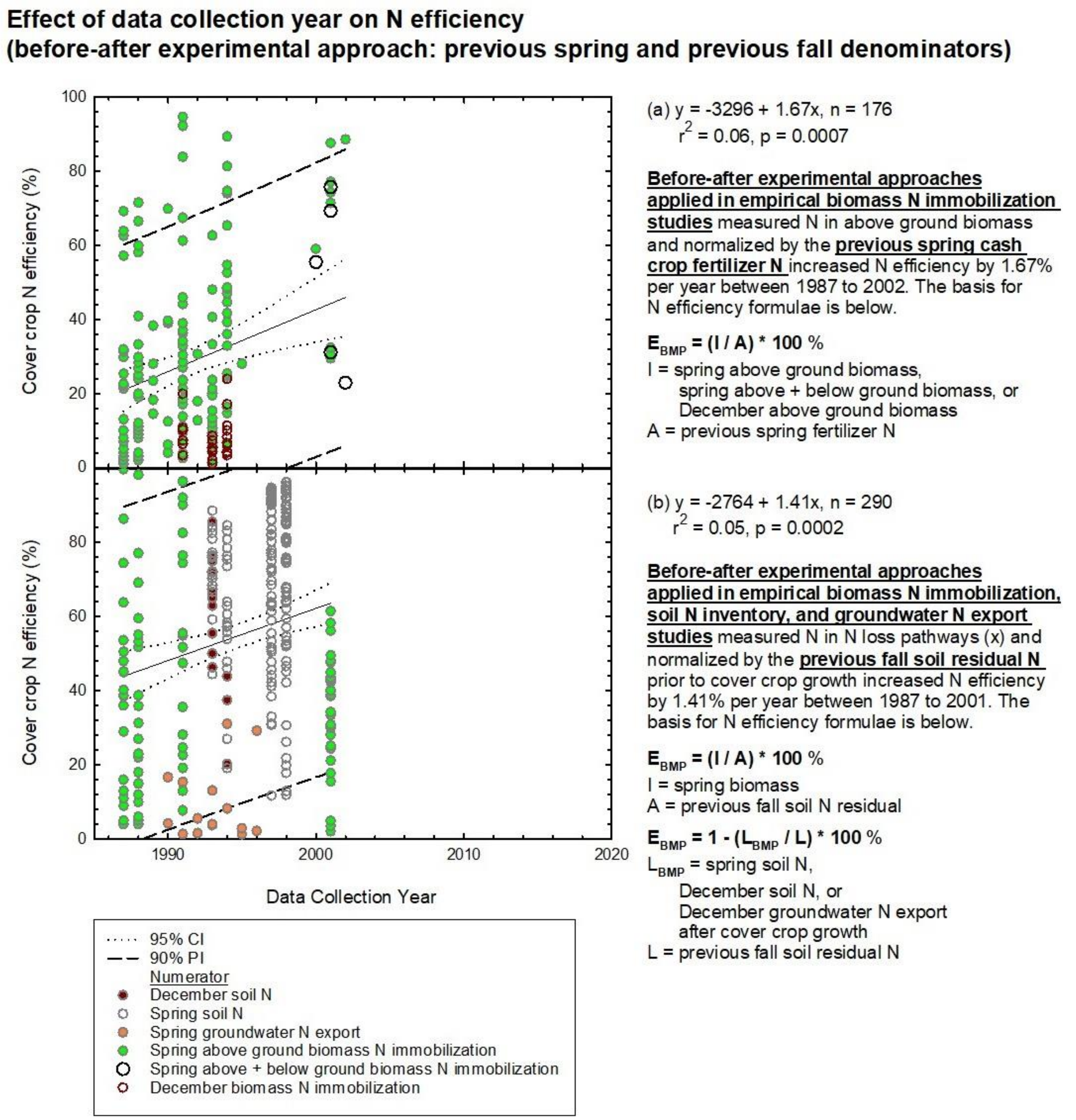


Figure 3.6. The cover crop N efficiency data are based on treatment methods compared to previous spring fertilizer applications (Fig. 3.6a, top) and previous fall soil residual N (Fig. 3.6b, bottom). Unless the reference stated the N efficiency, I adjusted the N content of below-ground biomass for empirical studies that measured non-legume cover crop immobilization. Confidence interval (CI) is the range where the regression line values, or slope, will fall 95% of the time for repeated measurements. Prediction interval (PI) is the range where the individual observation (y) will fall 90% of the time for repeated measures.

inverse relationship ($r^2 = 0.45$, $p = 0.01$, -2.9% yr^{-1}) between 9 y of cereal rye cover crop growth and N efficiencies based on BA immobilization experiments. The effect of consecutive years of cover crop growth on N efficiencies based on long-term studies by Hively et al. (2020) (Fig. 3.7b) and Staver et al. (1998) (Fig. 3.7c) revealed significant contrasting outcomes ($p = 0.04$). Based on the CT groundwater N export model, these significant relationships show declining N efficiencies over nine years based on empirical BA immobilization experiments and increasing N efficiencies over ten years.

The significant relationships also agree with earlier N efficiency findings (modeled > empirical in Table 3.7, CT > BA in Table 3.12), and additional t-tests show that the mean N efficiency of a 10-year CT groundwater model (66% ± 1.9) is significantly greater than a 9-year empirical BA immobilization study (27% ± 2.5) and 13-year empirical BA groundwater experiments (10% ± 2.7, $p < 0.001$, Table 3.19). Based on empirical BA immobilization experiments, the mean N efficiency of 13 y of consecutive growth (41% ± 8.5) appears significantly higher than nine years by a factor of 1.5 ($p = 0.046$). The t-test results also showed the mean N efficiency based on soil N inventory during seven years of consecutive cover crop growth among empirical BA studies ($n = 12$, 85% ± 2.4) is significantly greater than the following successive years of cover crop growth: one year ($n = 30$, 35% ± 4.8, $p < 0.001$), three years ($n = 170$, 43% ± 2.2, $p < 0.001$), and nine years ($n = 14$, 27% ± 2.5, $p < 0.001$). These results indicate that N efficiencies increased after seven years (observed in soil N) and 13 years (observed via immobilization) due to soil N depletion, and the slow depletion of groundwater N over ten years increased modeled N efficiencies. To review comparable median results based on Mann-Whitney tests, see Table K5.

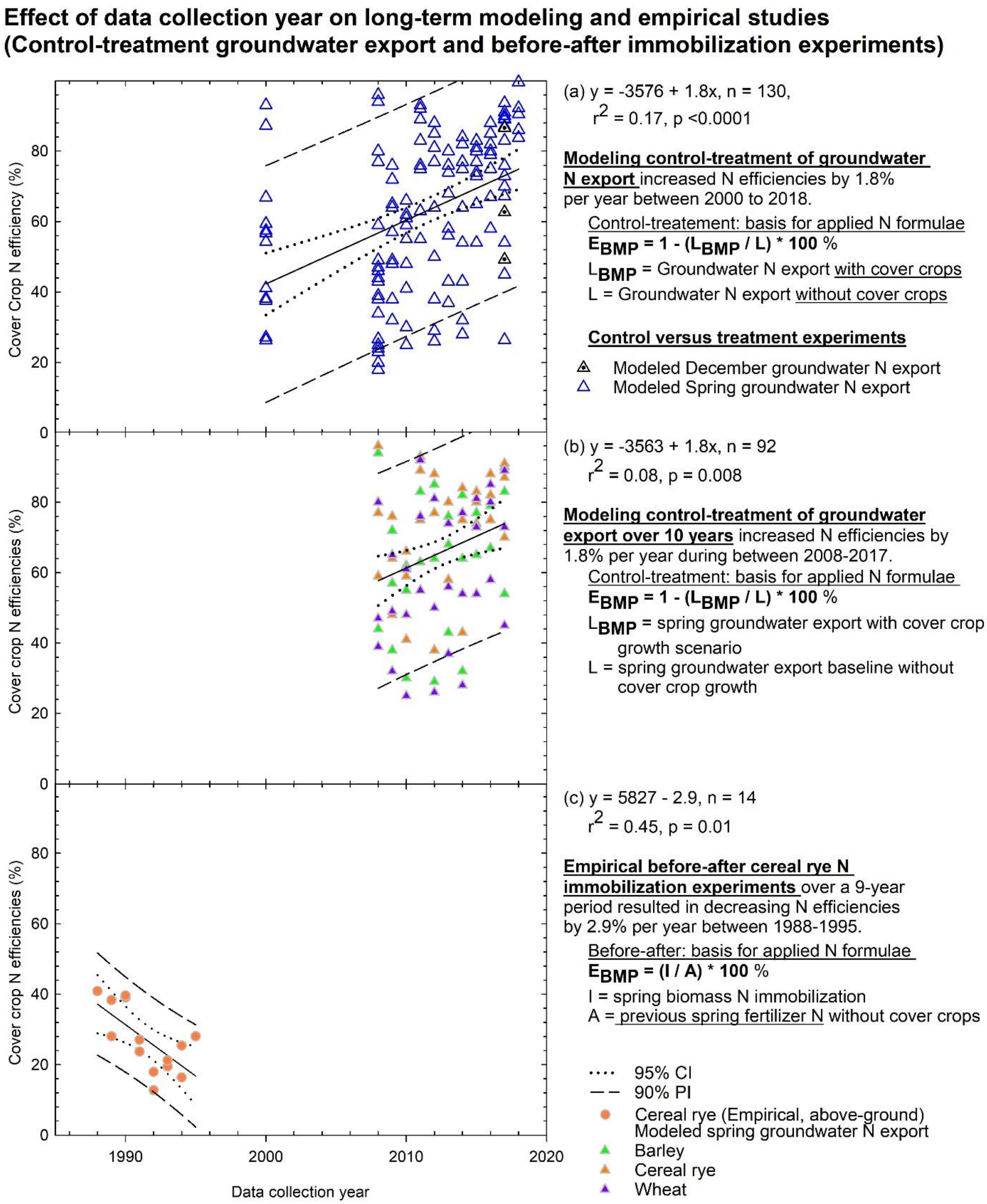


Figure 3.7. Most modeled control-treatment experiments are based on groundwater N export scenarios (top panel), and the majority of these N efficiencies are attributed to long-term modeling scenarios provided by Hively et al. 2020. Panel b (middle) depicts modeled data over a 10-year time frame from Hively et al. 2020. Panel c (bottom) displays N efficiency data collected during a 9-year empirical study by Staver et al. 1998 using before-after experiments to measure N immobilization in above-ground biomass during the spring. Confidence interval (CI) is the range where the regression line values, or slope, will fall 95% of the time for repeated measurements. Prediction interval (PI) is the range where the individual observation (y) will fall 90% of the time for repeated measures.

Table 3.19. Consecutive years of cover crop growth. Significance levels for t-test comparisons between years of consecutive cover crop growth. Abbreviations: “App” denotes empirical “E”and modeling “M” approach, “Variable” represents the classes of variables, “Interpretation” states the significance of the t-test, “n” means the sample size, “t-test” describes the results of the two-tailed p-value (p), t-statistic (t), corresponding degrees of freedom (df), “$\bar{x}$” represents the mean cover crop N efficiency expressed as a percent, “se” reflects the standard error, and “sd” represents the standard deviation.

				t-test					
App	**Variable**	**Interpretation**	**n**	**p**	**T**	**df**	**$\bar{x}$**	**se**	**sd**
	A comparison of consecutive years of cover crop growth								
E	1 yr		30				35	4.8	26
E	2 yr	2 yr (E) > 1 y (E)	218	0.001	-3.2	246	54	2.1	31
		2 yr (E) > 3 y (E)		< 0.001	3.5	386			
E	3 yr		170				43	2.2	29
E	7 yr (Soil N inventory)	7 yr (E) > 1 y (E)	12	< 0.001	6.5	40	85	2.4	8
		7 yr (E) > 3 y (E)		< 0.001	-5	36			
		7 yr (E) > 9 y (E)		< 0.001	16	24			
E	9 yr (Immobilization)		14				27	2.5	9
E	13 yr (Immobilization, I)	13 yr (E, I) > 13 y (E, G)	5	< 0.001	4.7	17	41	8.5	19
		13 yr (E, I) > 9 y (E)		0.046	2.1	17			
E	13 yr (Groundwater, G)		14				10	2.7	10
M	2 yr	2 yr (M) > 2 y (E)	28	< 0.001	-5.5	42	79	4.1	22
M	10 yr (Groundwater, G)	10 yr (M) > 9 y (E)	92	< 0.001	-7.6	104	66	1.9	19
		10 yr (M) > 13 y (E, G)		< 0.001	-11	104			

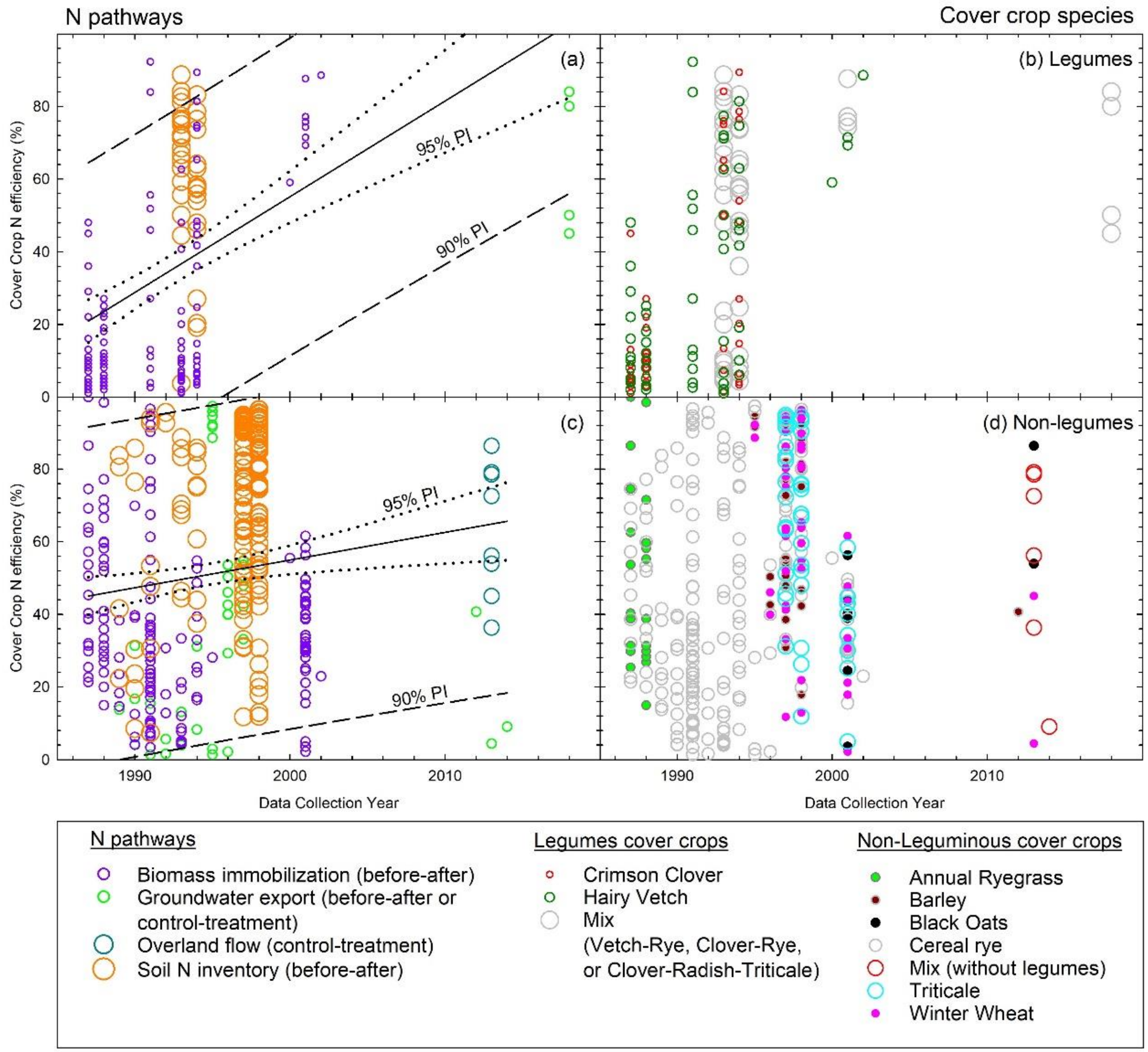
<u>Non-legume cover crop N efficiencies are greater than legume cover crop N efficiencies</u>

Empirical cover crop studies in the U.S. Coastal Plain Province evaluated a variety of cover crop species using BA and CT experimental methods (Figure 3.8). The effect of years had a significant positive increase on legume N efficiencies ($r^2 = 0.23$, $p < 0.001$, 2.6% yr^{-1}) and non-legume N efficiencies ($r^2 = 0.02$, $p = 0.006$, 0.76% yr^{-1}). The N efficiencies of legume cover crops (top row) increased 3.4 times faster than those of non-legume (bottom row) cover crops ($p < 0.001$). Additional statistical comparisons revealed (Table 3.20) that the mean N efficiency of non-legumes (51% ± 1.5) is significantly greater than the mean N efficiency of legume cover crop species (35% ± 2.4, $p < 0.0001$). T-tests showed that the mean N efficiencies between non-legume cover crops barley (n = 38, 69% ± 3.5) is significantly greater than cereal rye (n = 202, 44% ± 2) by a factor of 1.6 ($p < 0.001$) and wheat (n = 48, 59%± 4.1) is significantly greater than cereal rye by a factor of 1.1 ($p = 0.002$). To review comparable median results based on Mann-Whitney tests, review Table K6.

Overall, data collection years strongly affect N efficiencies based on legume and non-legume cover crops between 1987 and 2018, and t-tests indicate that barley and wheat mean N efficiencies are significantly higher than cereal rye cover crops. These findings are consistent with N efficiency t-tests reported in Table 3.12: Spring Soil N > Immobilization ($p < 0.001$) and CT groundwater > BA groundwater ($p < 0.001$). A comparison of N pathway panels a and c with cover crop species panels b and d indicates most cereal rye N efficiencies were based on empirical BA immobilization ($n = 122$) or groundwater N export ($n = 24$) experiments before 2001. Cereal rye CT and BA soil N experiments contributed ~31% of cereal rye N efficiencies ($n = 67$). Wheat and barley N efficiencies are based on BA soil N and CT groundwater or overland flow experiments.

Figure 3.8. The legume cover crop N efficiencies are displayed in panels a and b (top row) and non-legume cover crops are displayed in panels c and d (bottom row). Panel a and c (left panels) symbolizes N efficiencies based on the N pathways observed in the experimental approaches. Panel b and d (right panels) illustrates the wide distribution of N efficiencies based on legume (Fig. 3.8b) and non-legume (Fig. 3.8d) species over time. Confidence interval (CI) is the range where the regression line values, or slope, will fall 95% of the time for repeated measurements. Prediction interval (PI) is the range where the individual observation (y) will fall 90% of the time for repeated measures.

Positive effect of data collection years on N efficiencies of legume and non-legume cover crops (empirical method)



(a, b) $y = -5213 + 2.6x$, $n = 155$
$r^2 = 0.23$, $p < 0.001$

Empirical before-after and control-treatment experiments applied to legumes increased N efficiencies by 2.6% per year between data collection years 1987-2018. Legume species are symbolized in panel b.

(c, d) $y = 1473 + 0.76x$, $n = 369$
$r^2 = 0.02$, $p = 0.006$

Empirical before-after and control-treatment experiments applied to non-legume cover crops increased N efficiencies by 0.76% per year between 1987 and 2014. Non-legume species are symbolized in panel d. The basis of N efficiency formulae is below.

Before-after: basis for applied N formulae

E_{BMP} = **(I / A) * 100** %

I = spring or December (Dec.) N in biomass

A = previous spring fertilizer N or previoius fall soil residual N without cover crop growth

E_{BMP} = **1 - (L_{BMP}/ L) * 100** %

L_{BMP} = spring or Dec. N in groundwater export or soil inventory with cover crops

L = previous fall soil residual N or previous fall groundwater N lexport without cover crops

Control-treatment: basis for applied N formulae

E_{BMP} = **1 - (L_{BMP} / L) * 100** %

L_{BMP} = spring or Dec. N in overland flow, groundwater export or soil N inventories with cover crop growth

L = spring or Dec. N in overland flow, groundwater export or soil N inventories without cover crops

Table 3.20. T-tests of legumes and non-legumes group means. Abbreviations: “Appt” denotes empirical “E” and modeling “M” approach, “Variable” represents the classes of variables, “Interpretation” states the significance of the t-test, “n” means the sample size, “t-test” describes the results of the two-tailed p-value (p), t-statistic (t), corresponding degrees of freedom (df), “$\overline{x}$” represents the mean cover crop N efficiency expressed as a percent, “se” reflects the standard error, and “sd” represents the standard deviation.

				t-test					
App	**Variable**	**Interpretation**	**n**	**p**	**t**	**df**	**$\overline{x}$**	**se**	**sd**
	A comparison of legumes and non-legumes								
E	Non-leg.	Non-leg. (E) > Legume (E)	369	< 0.0001	5.7	522	51	1.5	28
E	Legume		155				35	2.4	30
	A comparison of non-legume cover crop plant species								
E	Annual ryegrass (A. rye)	A. rye (E) = C. rye (E)	24	0.212	1.3	224	52	4.8	24
E	Barley	Barley (E) > C. rye (E)	38	< 0.001	6	64	69	3.5	22
		Barley (E) > Barley (M)		0.1	1.7	76			
E	Cereal rye (C. rye)		202				44	2.0	29
E	Wheat	Wheat (E) > C. rye (E)	48	0.002	-3.1	248	59	4.1	28
		Wheat (E) > Wheat (M)		0.004	2.9	103			
M	Barley		40				61	3.3	21
M	C. rye	C. rye (M) > C. rye (E)	50	< 0.001	-7.4	102	71	2.9	21
M	Wheat		57				44	3.3	25

Summary of data collection years' effect on cover crop N efficiencies

This section showed strong positive effects of the data collection year on cover crop N efficiency based on empirical and modeling studies between 1987-2018 (Fig. 3.5). These data also show strong positive effects of the data collection year on cover crop N efficiency based on BA and CT experimental methods between 1987-2018, with BA empirical methods increasing more than 2 times faster than CT methods. Figure 3.6 showed that the N efficiencies calculated based on the previous fall soil residual N or previous spring fertilizer N denominators increased at the same rate between 1987 and 2002; however, significant differences between the adjusted means indicate higher N efficiencies are associated with the previous fall soil residual N denominator in the Coastal Plain Region. The data in Figure 3.7a illustrated strong positive effects of the data collection year on cover crop N efficiency based on modeled CT experiments of groundwater export between 2000-2018. Most of this data is attributed to a long-term CT groundwater export model (Fig. 3.7b), significantly increasing with data collection years. In contrast, rye cover crop N efficiencies based on empirical BA immobilization experiments decreased over nine years (Fig. 3.7c). These results indicate that consecutive years of cover crop growth reduce the reported empirical observations of N efficiencies due to N immobilization, and increasing modeled N efficiencies are attributed to the slow depletion of groundwater N. Figure 3.8 shows data collection years strongly affect N efficiencies based on legume and non-legume cover crops between 1987 and 2018, and T-tests indicate that barley and wheat mean N efficiencies are significantly higher than cereal rye cover crop.

3.3.5 The effects of growing days on cover crop N efficiencies

In the following section, I present significant relationships between the cover crop N efficiencies and growing days to explain the wide variability depicted in Figure 3.4b. This section presents the significant relationships between days and N efficiencies based on empirical research using before-and-after (BA) and control versus treatment (CT) experiments (Fig. 3.9a) and modeling CT experiments (Fig. 3.9b). I then focus on a series of comparisons between days and BA experiments used in empirical studies. For example, Figure 3.9c depicts the effect of days on N efficiencies based on empirical N immobilization observations normalized by the previous spring cash crop fertilizer N. Additional N pathways were normalized by the previous fall soil residual N (Fig. 3.10). Figure 3.11 illustrates the effect of days on modeling and empirical CT experiments of groundwater export. I also present the effect of days on N efficiencies influenced by empirical BA and modeling CT experiments of non-leguminous cover crops (Fig. 3.12). Figure 3.13 shows the effects of more than 150 growing days on N efficiencies based on empirical BA immobilization experiments. The significant relationships between growing days and N efficiencies based on the N pathways and N inputs measured in empirical and modeled BA and CT experiments are summarized in Table 3.21.

Table 3.21. Slope analysis of linear regression models depicting time trends (growing days) of cover crop N efficiency variables. A summary of numerator and denominator variables used in cover crop N efficiency experimental approach during growing days. Significant relationships are described by a linear regression and slope comparison interpretation. Abbreviation: "Fig." represents the figure number, "Met." identifies the research approach, empirical (E) or modeling (M), and experimental methods before-after (BA) or control-treatment (CT), the "Numerator" lists the N with cover crop growth and the "Denominator" lists the N measurement without cover crop growth, "n" represents the sample size, "y-int" represents the y-intercept, "Slope" denotes the coefficient, "Interp (p)" references the figure that depicts slopes compared, interpretation of the slope comparison, and p-value, "r^2" represents the linear regression model r-squared value, "p" represents the p-value of the regression coefficient, and "days" represents the range of growing days.

	N efficiency formulae variables									
Fig.	**Met**	**Numerator**	**Denominator**	**n**	**y-int**	**Slope**	**Interp (p)**	**r^2**	**p**	**days**
	Research methods: Empirical and Empirical									
9a	M, CT	Scenario w/ cover crop (CC)	Baseline w/o CC	165	38	0.14	**9a = 9b**	0.03	0.03	84-266
		Sp. direct pathways (DP)	Sp. DP							
		Sp. or Dec. soil N	Sp. or Dec. soil N							
		Sp. or Dec. Gw N export	Sp. or Dec. Gw N export							
9b	E, BA	Sp. above-ground biomass N	Prev. sp. fertilizer (fert) N	524	14.5	0.18		0.08	< 0.001	69-261
		Sp above + below ground bio.	Prev. fall soil residual (resid) N							
		Sp. above-gr. (ΔNI)	Prev. fall soil resid N + 80 kg N							
		Dec. biomass N								
	E, CT	Sp. groundwater (Gw) export	Prev. fall Gw export							
		Sp. soil N inventory (inv)	Sp. soil N							
		Sp. overland flow	Sp. overland flow							
		Dec. soil N inv	Prev. fall soil resid N							
	Empirical **before-after experimental approach**									
9c	E, BA	Biomass N immobilization:	Prev. sp. fert N	94	-2.9	0.20	n/a	0.18	< 0.0001	69-232
		Sp. above-ground (gr.)								
		Sp. above- and below-gr								
		Dec. above-gr.								
10a	E, BA	Sp. soil N inv	Prev. fall soil resid N	131	108	-0.17	10a ≠ 10b (< 0.0001)	0.11	0.000	159-261
10b	E, BA	Sp. above-gr. biomass	Prev. fall soil resid N	36	-69	0.65	10a ≠ 10c (< 0.0001)	0.47	< 0.0001	160-221
10c	E, BA	Sp. above-gr. (ΔNI)	Prev. fall soil resid N + 80 kg N	36	-7	0.30	**10b = 10c**	0.51	< 0.0001	78-194

Table 3.21 (continued). Slope analysis of linear regression for growing days and N efficiency.

	N efficiency formulae variables									
Fig.	**Met**	**Numerator**	**Denominator**	**n**	**y-int**	**Slope**	**Interp (p)**	**r^2**	**p**	**days**
	Empirical and Modeled control-treatment experimental approach									
		With cover crops	Without cover crops							
11a	M, CT	DP	DP	21	127	-0.56	n/a	0.33	0.006	134-194
11b	M, CT	Sp. Gw export	Sp. Gw export	130	6.3	0.37	**11b = 11c**	0.20	< 0.0001	84-266
11c	E, CT	Sp. Gw export	Sp. Gw export	24	-151	0.95		0.21	0.02	172-227
12b	M, CT	Sp. soil N inv	Sp. soil N inv	14	44	0.20	12b ≠ 12d	0.30	0.04	84-266
12d	E, CT	Sp. soil N inv	Sp. soil N inv	22	238	-1.1	(< 0.0001)	0.58	< 0.0001	150-203
	Empirical before-after experimental approach: Winter Wheat									
12a	E, BA	Sp. soil N inv	Prev. fall soil resid N	31	121	-0.24	12a ≠ 12c	0.16	0.02	173-261
12c	E, BA	Sp. above-gr. (ΔNI)	Prev. fall soil resid N + 80 kg N	9	-25	0.41	(0.03)	0.64	0.01	78-194
	Empirical before-after immobilization experimental approach: 150 growing days or more									
13a	E, BA	Sp. above-gr.	Prev. fall soil resid N	36	-69	0.65	13a ≠ 13c	0.47	< 0.0001	160-221
13b	E, BA	Sp. above-gr. (ΔNI)	Prev. fall soil resid N + 80 kg N	12	-39	0.46	(0.01) **13a = 13b**	0.34	0.05	159-194
13c	E, BA	Sp. above-gr.	Prev. sp. fert N	60	-11.4	0.23	**13b = 13c**	0.09	0.02	150-184

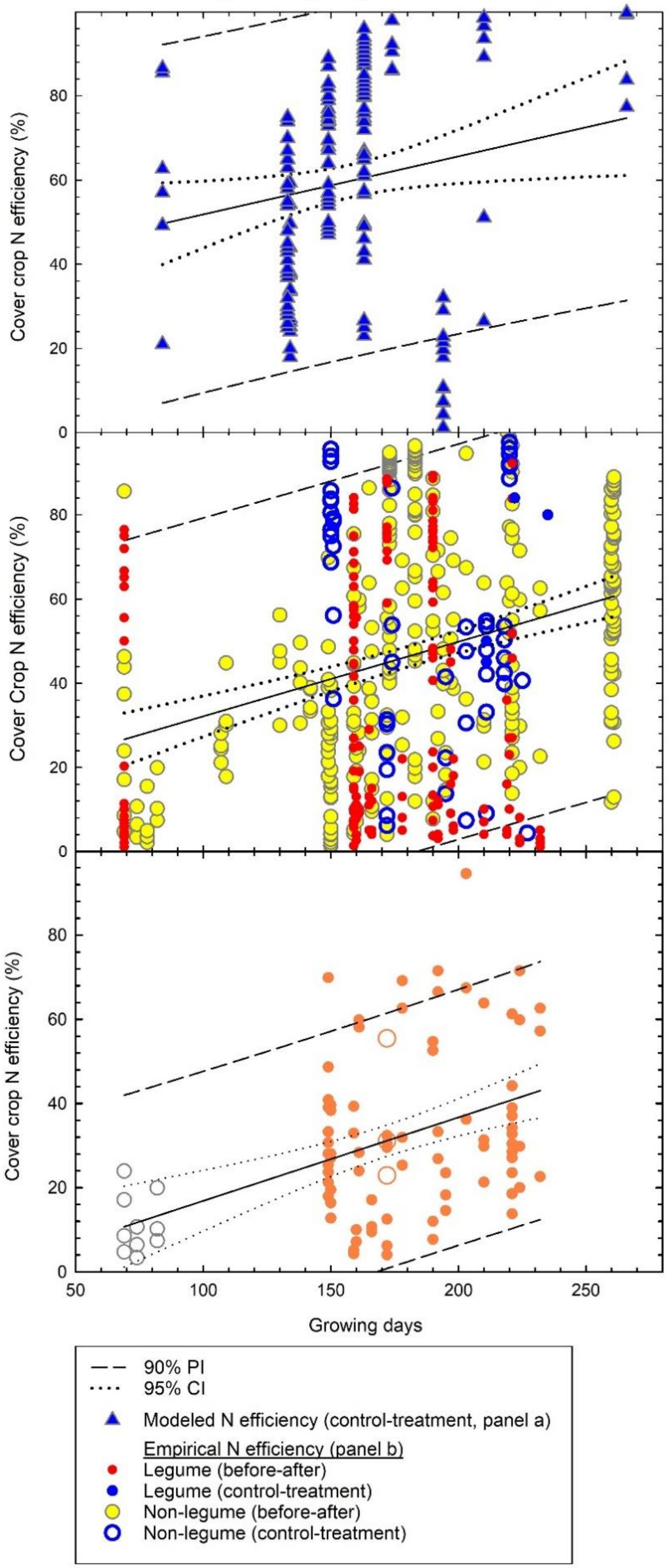
Positive effects attributed to empirical and modeling experimental methods

Figure 3.9 illustrates the significant positive effects of growing days on modeled CT N efficiencies ($p = 0.03$, Fig. 3.9a) and empirical BA and CT N efficiencies ($p < 0.001$, Fig. 3.9b). An ANCOVA equal slopes test detected no significant differences between the modeling slope and empirical slope ($b = 0.17\%\ d^{-1}$, Table K7). A subsequent analysis of the equal slopes models revealed that there is a significant difference in the adjusted means between the empirical (adj. $\bar{x} = 45.5\% \pm 1.2$, CI[43.1,47.9]) and modeling (adj. $\bar{x} = 63\% \pm 2.2$, CI[58.5, 67.1]) mean N efficiencies ($t = 6.8$, $p < 0.001$). These results indicate that modeled cover crop N efficiencies reflect the empirical N efficiency slope between growing days 69 – 266. However, the model-adjusted mean N efficiency is significantly greater than the empirical by a factor of 1.4, and this bias could overestimate modeled water quality improvements in the Coastal Plain where modeled cover crop N efficiencies are integral.

The remaining plots in this section show the effect of growing days on non-legume cover crop N efficiencies to remove a bias of lowered N efficiencies due to legume cover crops shown in Figure 3.8 and is supported by t-test results, non-legume > legume ($p < 0.0001$, Table 3.20). Figure 3.9c depicts N efficiencies of non-leguminous cover crops based on three types of empirical BA immobilization experiments normalized by the previous spring cash crop fertilizer N: (1) spring samples of above-ground biomass N concentration, which were subsequently adjusted for below-ground N content, (2) spring samples of N concentration measured directly from above- and below-ground biomass, and (3) measures of N from above-ground biomass measured in December. The effect of days has a significant positive increase ($r^2 = 0.18$, $p < 0.0001$, $0.20\%\ d^{-1}$) on all types of BA immobilization experiments between growing days 69 and 232, and the regression indicates the mean N efficiency does not exceed 40%.

Figure 3.9. The cover crop N efficiency data are based on two methods relative to growing days. The top panel (Fig. 3.9a) illustrates before-after and control-treatment experiments applied to non-legumes and legume cover crops used in empirical studies. The middle panel (Fig. 3.9b) presents control-treatment scenarios used in modeling studies. Panel c (bottom panel) depicts the cover crop N efficiencies calculated based on before-after experiments compared to previous spring fertilizer applications. Unless the reference stated the N efficiency, I adjusted the N content of below-ground biomass for empirical studies that measured non-legume cover crop immobilization. Confidence interval (CI) is the range where the regression line values, or slope, will fall 95% of the time for repeated measurements. Prediction interval (PI) is the range where the individual observation (y) will fall 90% of the time for repeated measures.

Positive effect of growing days on cover crop N efficiency (empirical and modeling methods)



(a) $y = 38 + 0.14x$, $n = 165$
$r^2 = 0.03$, $p = 0.03$

Modeling methods using control-treatment experiments increased N efficiencies by 0.14% per day between growing days 84 to 266. The basis of N efficiency formulae are below.

(b) $y = 14.5 + 0.18x$, $n = 524$
$r^2 = 0.08$, $p <0.001$

Empirical methods using before-after and control-treatment experimental approaches increased N efficiencies by 0.17% per day between growing days 69 to 261. The basis of N effiicency formulae are below.

Before-after: basis for applied N formulae

$E_{BMP} = (I / A) * 100$ %

I = spring or December N sampled in biomass
A = previous spring fertilizer N or previous fall soil residual N without cover crop growth

$E_{BMP} = 1 - (L_{BMP} / L) * 100$ %

L_{BMP} = spring or December N sampled in groundwater export or soil with cover crop growth
L = previous fall soil residual N or previous groundwater N export without cover crop growth

Control-treatment: basis for applied N formulae

$E_{BMP} = 1 - (L_{BMP} / L) * 100$ %

L_{BMP} = spring or December N sampled in direct pathways, overland flow, groundwater export or soil N inventories with cover crop growth
L = spring or December N sampled in direct pathways, overland flow, groundwater export or soil N inventories without cover crop growth

(c) $y = -2.9 + 0.20x$, $n = 94$
$r^2 = 0.18$, $p < 0.0001$

Before-after experimental approaches applied in empirical N immobilization studies of above-ground non-legume cover crops normalized the **previous spring cash crop fertilizer N** increased N efficiency by 0.20% per day between growing days 69 to 232. The basis for N efficiency formulae is below.

$E_{BMP} = (I / A) * 100$ %

Formula abbreviations and panel c legend

I = ● Spring above-ground biomass
○ December above-ground biomass
○ Spring above- and below-ground biomass

A = previous spring cash crop fertilizer N

Variable effects attributed to empirical before-after soil N and immobilization experiments

Figure 3.10 displays cover crop N efficiencies based on the empirical BA experiments of soil N inventories and immobilization N pathways (numerator) normalized by the previous fall soil residual N (denominator). The top panel shows growing days between 159 and 261 have a significant inverse relationship ($r^2 = 0.11$, $p = 0.0001$, $-0.17\%\ d^{-1}$) with N efficiencies based on spring soil N inventories. In contrast, the effect of 78 and 221 growing days on N efficiencies based on spring above-ground biomass (Fig. 3.10b, $r^2 = 0.47$, $p = 0.001$, $0.65\%\ d^{-1}$) and spring above-ground biomass (ΔNI) (Fig. 3.10c, $r^2 = 0.51$, $p < 0.001$, $0.30\%\ d^{-1}$) is a highly significant increase. A statistical comparison of the slopes (-0.17, 0.65, and 0.30) in panels a, b, and c resulted in significant differences between panels a and b ($p < 0.0001$) and panels a and c ($p < 0.0001$). An equal slopes test conducted in ANCOVA detected no significant differences between the slopes in Figures 3.10b and 3.10c ($b = 0.38\%\ d^{-1}$, Table K7). A subsequent analysis of the equal slopes models indicates that the adjusted mean of panel c (adj. $\bar{x} = 48 \pm 4.6$, CI[38.9, 57.1]) is significantly greater than panel b (adj. $\bar{x} = 32.7 \pm 3.1$, CI[26.4, 38.9]) by a factor of 1.5 ($t = 2.4$, $p = 0.017$). These data show increasing N efficiencies between growing days 78 and 221 due to available plant N, and the subsequent decreasing N efficiencies between growing days 159 to 261 due to soil N depletion.

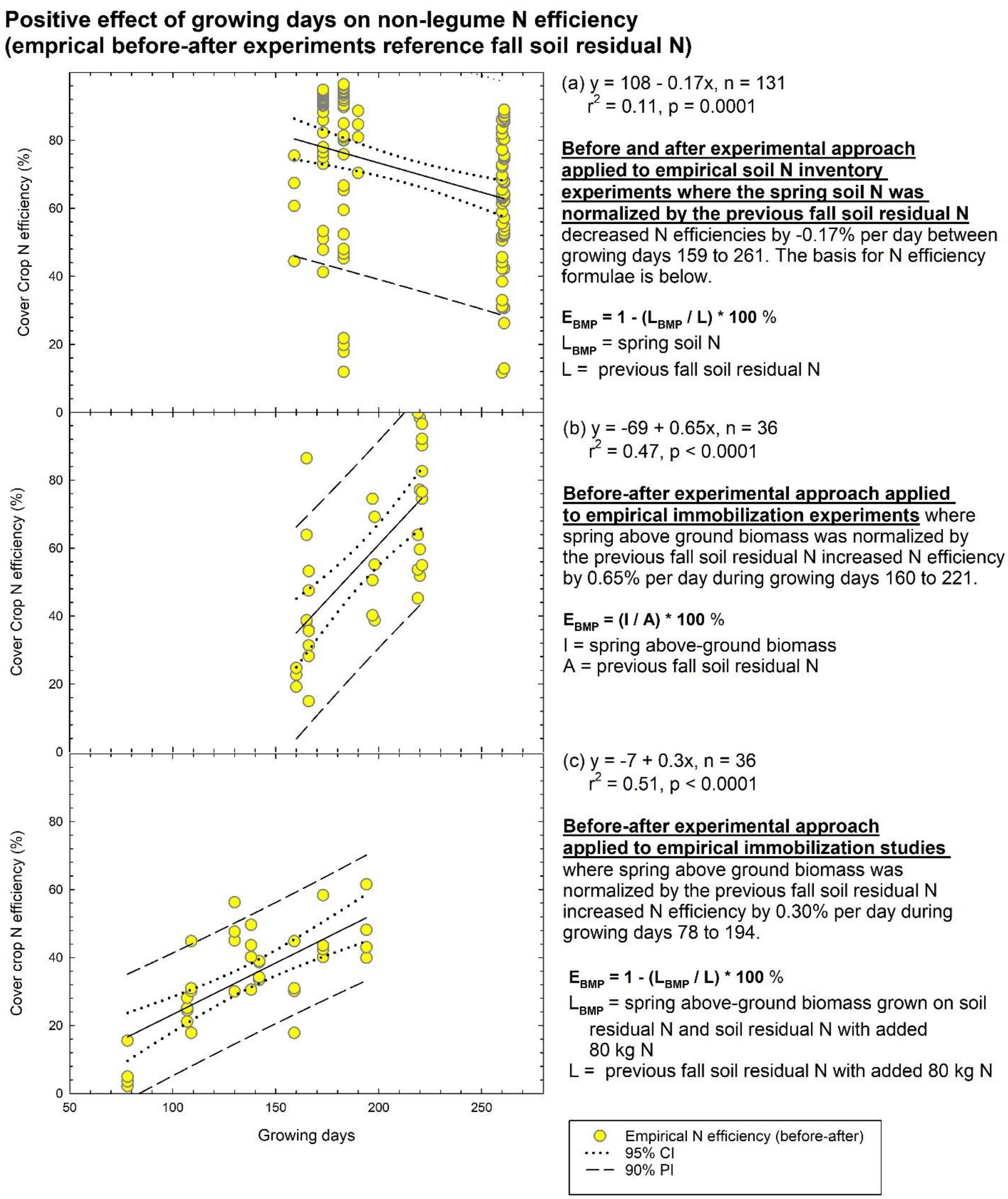


Figure 3.10. The N efficiency is based on empirical before-after experiments that were normalized by the fall soil residual N. Each panel reflects a different numerator. Figure 3.10a (top) illustrates spring soil N inventories. Figure 3.10b (middle) depicts spring above-ground biomass. Figure 3.10c (bottom) shows the spring sample of above-ground biomass grown on fall residual soil N or fall residual soil N with added 80 kg N (ΔNI). Unless the reference stated the N efficiency, I adjusted the N content of below-ground biomass for empirical studies that measured non-legume cover crop immobilization. Confidence interval (CI) is the range where the regression line values, or slope, will fall 95% of the time for repeated measurements. Prediction interval (PI) is the range where the individual observation (y) will fall 90% of the time for repeated measures.

Variable effects due to modeling and empirical control versus treatment experiments

Figure 3.11 shows CT experiments used in modeling direct pathways (Fig. 3.11a), groundwater N export (Fig. 3.11b), and empirical groundwater N export (Fig. 3.11c). Figure 3.11 a illustrates a significant inverse relationship ($r^2 = 0.33$, $p = 0.006$, -0.56% d^{-1}) between modeled CT direct pathway experiments and the number of growing days between 134 and 194. In contrast, the effect of 84 to 266 growing days had a significant positive increase with N efficiencies based on modeled spring and December groundwater N export ($r^2 = 0.20$, $p < 0.0001$, 0.37% d^{-1}) and empirical spring groundwater N export ($r^2 = 0.21$, $p = 0.02$, 0.95% d^{-1}). ANCOVA equal slopes test results detected no significant differences between the slopes in Figures 3.11b and 3.11c (b = 0.40% d^{-1}, Table K7). A subsequent analysis of the equal slopes models revealed that the modeled adjusted mean (adj. $\overline{x} = 67 \pm 1.9$, CI[63.1, 70.7]) is significantly greater than the empirical adjusted mean (adj. $\overline{x} = 30.3 \pm 5.5$, CI[19.3, 41.2]) by a factor of 2.2 ($t = 5.9$, $p < 0.001$). T-test comparisons of modeled (Fig. 3.11b) and empirical (Fig. 3.11c) mean N efficiencies after 170 growing days revealed the modeled mean N efficiency ($n = 9$, $\overline{x} = 85 \pm 7.5$) is significantly greater than the empirical ($n = 24$, $\overline{x} = 51 \pm 5.9$) by a factor of 1.7 ($p = 0.004$). These data reveal no statistical difference in slope between modeled and empirical CT groundwater experiments; however, modeled N efficiencies are significantly higher than empirical N efficiencies, which is consistent with t-test results reported in Table 3.12 (Model CT groundwater > Empirical CT groundwater, $p = 0.03$).

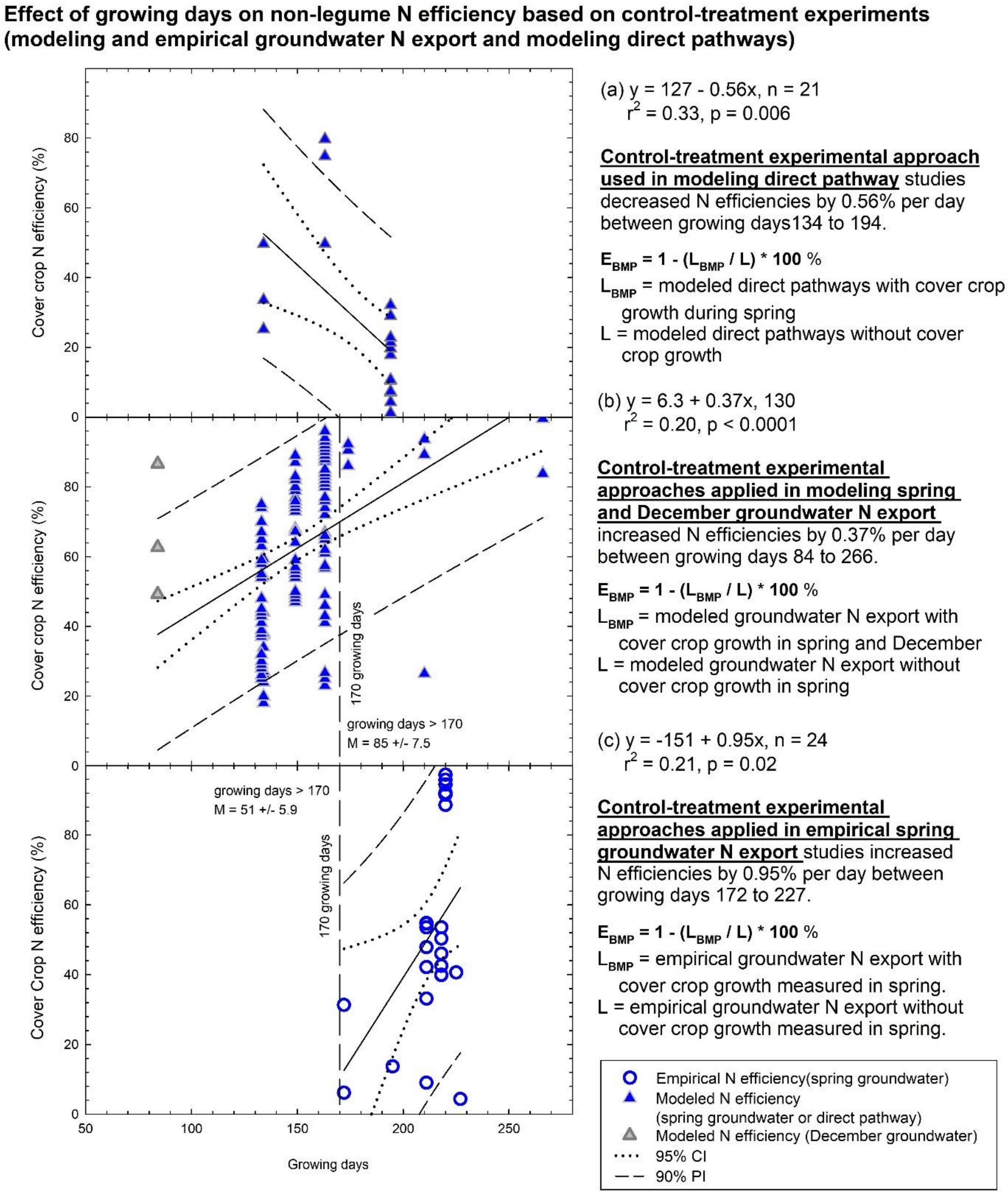


Figure 3.11. The N efficiency is based on modeled direct pathway studies using control-treatment methods. Direct pathways include overland flow, lateral flow, and groundwater (Fig. 3.11a, top). The N efficiency is based on control-treatment experiments in modeling spring and December groundwater N export studies (Fig, 3.11b, middle) and empirical spring groundwater N export studies (Fig, 3.11c, bottom). Confidence interval (CI) is the range where the regression line values, or slope, will fall 95% of the time for repeated measurements. Prediction interval (PI) is the range where the individual observation (y) will fall 90% of the time for repeated measures.

Contrasting effects of growing days on N efficiencies: BA and CT soil N experiments

Figure 3.12 shows N efficiencies from empirical BA immobilization and soil N inventory experiments using winter wheat (left column) and modeling and empirical CT non-legume soil N experiments (right column). The effect of days between 78 and 266 days had a significant positive increase in N efficiencies based on winter wheat N immobilization (ΔNI) normalized by the previous fall soil residual N + 80 kg N ($r^2 = 0.64$, $p = 0.01$, 0.41% d^{-1}, Fig. 3.12a) and modeled CT soil N inventory experiments ($r^2 = 0.30$, $p = 0.04$, 0.20% d^{-1}, Fig. 3.12b). In contrast, days between 150 and 261 had a significant inverse effect on N efficiencies from empirical BA soil N inventory experiments ($r^2 = 0.16$, $p = 0.02$, -0.24% d^{-1}, Fig. 3.12c) and empirical CT soil N inventory experiments ($r^2 = 0.58$, $p < 0.0001$, -1.1% d^{-1}, Fig. 3.12d).

The ANCOVA equal slopes test results detected no significant differences between the slopes in panels a and b ($b = 0.24\ d^{-1}$, Table K7). A subsequent analysis of the equal slopes models revealed the adjusted mean N efficiency of model CT soil N in panel b (73 ± 4.7, CI[63.4, 82.8]) is significantly greater than empirical BA immobilization in panel a (34.6 ± 6.5, CI[21, 48]) by a factor of 2 ($t = 4.8$, $p < 0.001$). Additional slope comparison found significant differences between Figures 12a and 12c (0.41, -0.24, $p = 0.03$), Figures 12b and 12d (0.20, -1.1, $p < 0.0001$), and Figures 12c and 12 d (-0.24, -1.1, $P < 0.001$).

Winter wheat illustrates the expected increase in N efficiencies as nutrient uptake increases with plant tissue and root development (Fig. 3.12a) and the subsequent decline in N efficiency as plant-available soil N becomes exhausted after 150 growing days (Fig. 3.12c and 3.12d). However, the CT soil N export models do not account for soil N depletion since the mean N efficiencies on non-legume cover crops increase between 84 and 266 growing days (Fig. 3.12b), and this could have implications for water quality modeling efforts in the Coastal Plain.

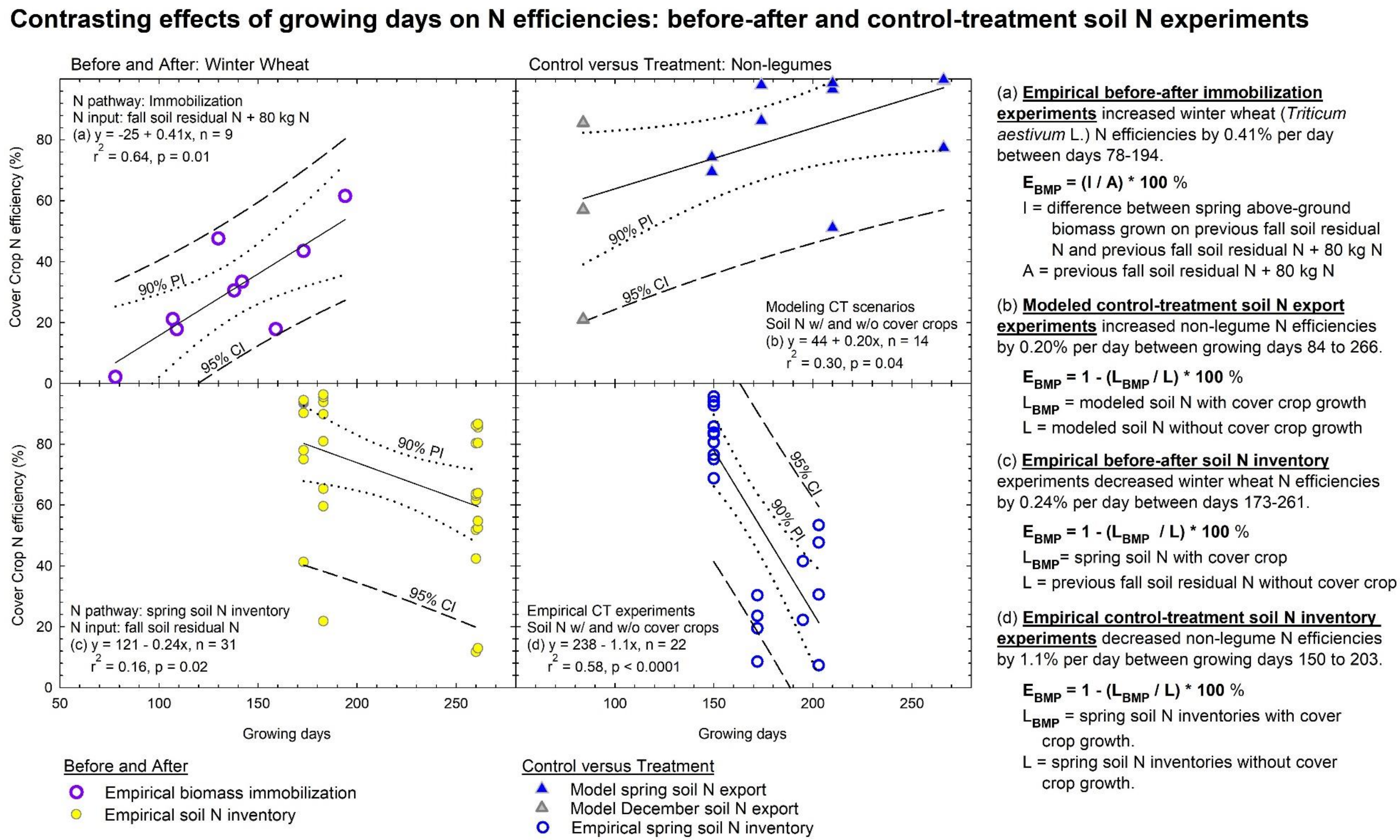


Figure 3.12. The N efficiencies of winter wheat shown in Figures 3.12a and 3.12b (left column) are based on empirical before-after N immobilization (Fig. 3.12a) and soil N inventory experiments (Fig. 3.12c). The N efficiencies of non-legume cover crops shown in Figures 3.12b and 3.12d (right column) are based on modeling control-treatment spring and December soil N export (Fig. 3.12b) and empirical control-treatment spring soil N inventory experiments (Fig. 3.12d). Unless the reference stated the N efficiency, I adjusted the N content of below-ground biomass for empirical studies that measured non-legume cover crop immobilization. Confidence interval (CI) is the range where the regression line values, or slope, will fall 95% of the time for repeated measurements. Prediction interval (PI) is the range where the individual observation (y) will fall 90% of the time for repeated measures.

N efficiency after 150 growing days: Spring immobilization of non-legume cover crops

Figure 3.13 shows the N efficiencies of non-legume cover crops after 150 days of growth from empirical BA immobilization experiments normalized by three N inputs. The effect of more than 150 growing days had a significant positive increase on the N efficiencies of annual rye and cereal rye (Fig. 3.13a, $r^2 = 0.47$, $p < 0.001$, 0.64% d^{-1}), triticale, winter wheat, cereal rye, and black oats (ΔNI) (Fig. 3.13b, $r^2 = 0.34$, $p = 0.05$, 0.46% d^{-1}), and cereal rye (Fig. 3.13c, $r^2 = 0.09$, $p = 0.02$, 0.23% d^{-1}). The N efficiencies increased 2.8 times faster in Figure 3.13a than Figure 3.13c (p=0.01).

The ANCOVA equal slopes test results detected no significant differences between the slopes in panel a and panel b ($b = 0.63$ d^{-1}, Table K7). A subsequent analysis of the equal slopes models revealed no significant difference between intercepts in panels a and b (53 ± 3.3). Therefore, the regression of the combined data set (panels a and b) is $y = -70 + 0.65x$, ($n = 48$, $r^2 = 0.50$, $p < 0.0001$). Additional equal slopes tests indicated no significant differences between slopes in panels b and c ($b = 0.24$ d^{-1}, Table K7). A subsequent analysis of the equal slopes models revealed that the adjusted mean in panel b (44 ± 5.3, CI[33.5, 54.5]) is significantly greater than panel c (30 ± 2.3, CI[25.7, 35]) by a factor of 1.5 ($t = 2.4$, $p = 0.021$).

These cover crop immobilization studies indicate continued nutrient uptake by cover crops if growing days are extended beyond 150 days of growth. This could mean earlier cover crop planting dates are needed to extend the cover crop growing season to achieve higher N efficiencies.

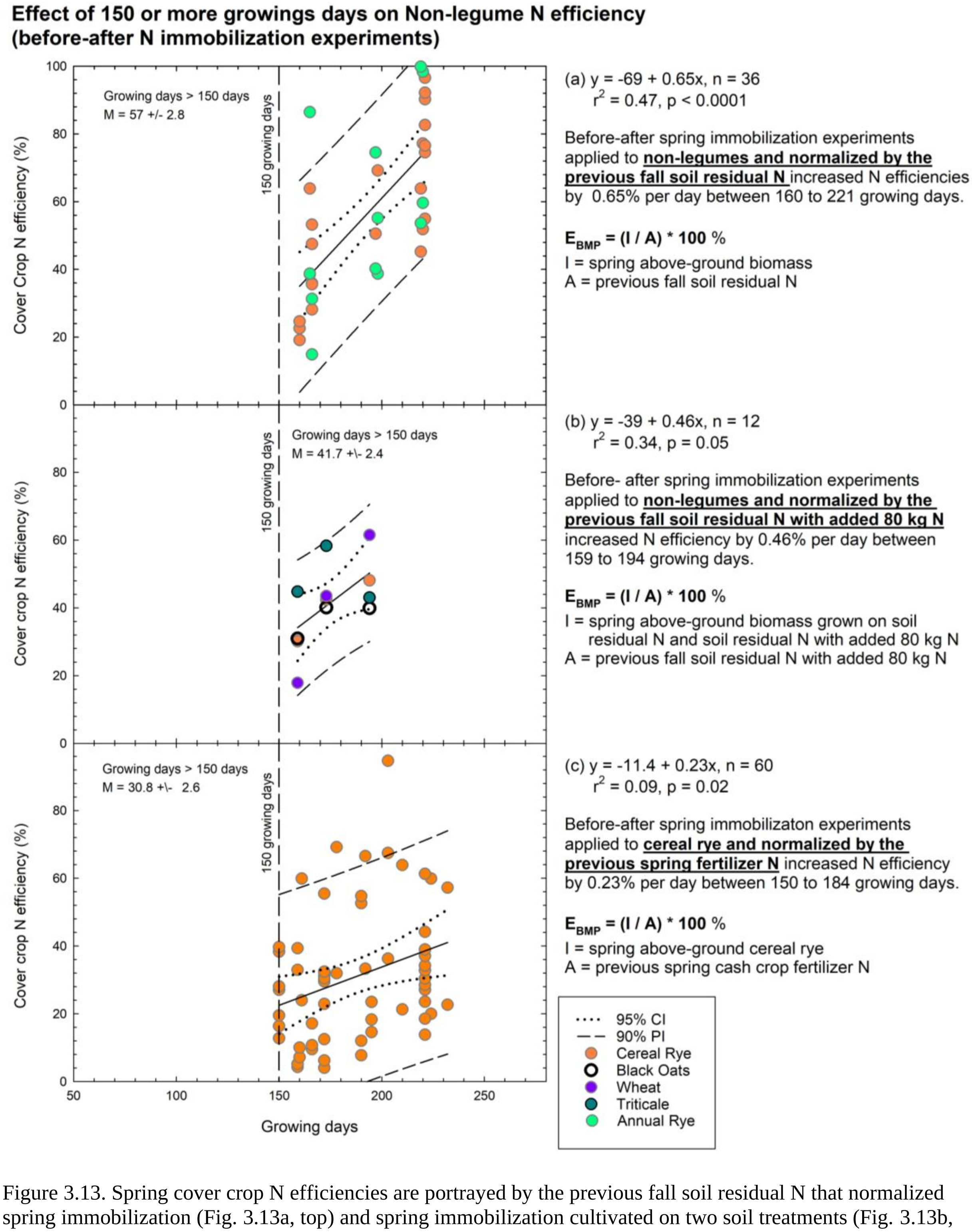


Figure 3.13. Spring cover crop N efficiencies are portrayed by the previous fall soil residual N that normalized spring immobilization (Fig. 3.13a, top) and spring immobilization cultivated on two soil treatments (Fig. 3.13b, middle), and the immobilization of cereal rye normalized by the previous spring fertilizer N (Fig. 3.13c, bottom). Unless the reference stated the N efficiency, I adjusted the N content of below-ground biomass for empirical studies that measured non-legume cover crop immobilization. Confidence interval (CI) is the range where the regression line values, or slope, will fall 95% of the time for repeated measurements. Prediction interval (PI) is the range where the individual observation (y) will fall 90% of the time for repeated measures.

Summary of growing days' effects on cover crop N efficiencies

In this section, I showed the slope of empirical and modeled cover crop N efficiencies are the same. However, the modeled mean N efficiency is significantly greater than the empirical mean N efficiency, which is consistent with t-test results reported in Table 3.12, Model CT groundwater > Empirical CT groundwater ($p = 0.03$, Figs. 3.9 and 3.11). This bias could overestimate the impacts of modeled cover crops and have consequences for water quality improvement efforts in the Coastal Plain Province. Figure 3.9c shows the relatively low N efficiencies from empirical BA immobilization normalized by previous spring fertilizer N, which did not exceed 40%, and this supports t-test results reported in Table 3.12, previous fall soil residual N > previous spring fertilizer N and spring soil N > immobilization ($p < 0.001$). Figure 3.10 depicts increasing N efficiencies based on the common N input, previous fall soil residual N, between growing days 78 and 221 due to available plant N, and the subsequent decreasing N efficiencies between growing days 159 to 261 due to soil depletion. Figure 3.12 shows the expected increase in N efficiencies as nutrient uptake increases with winter wheat tissue and root development and the subsequent decline in N efficiency as plant-available soil N becomes exhausted after 150 growing days. However, the CT soil N export models do not account for soil N depletion since the mean N efficiencies on non-legume cover crops increase between 84 and 266 growing days, and this could have implications for water quality modeling efforts in the Coastal Plain. Figure 3.13 illustrates continued N uptake by cover crops if growing days are extended beyond 150 days of growth. This could mean earlier cover crop planting dates are needed to extend the cover crop growing season to achieve higher N efficiencies.

3.4 Discussion

I conducted an in-depth quantitative assessment of 689 cover crop N efficiencies based on 18 published studies and multiple variables explaining why cover crop N efficiencies range widely across the U.S. Coastal Plain Province. Significant relationships between time and the historical records of cover crop N efficiencies are portrayed via publishing date (Fig. 3.3), data collection year (Fig. 3.4a), growing days (Fig. 3.4b), and spring growing days between days 150 and 280 (Fig. 3.13). These strong relationships emerged despite the influence of other variables. This approach provided a systematic process to comprehensively examine the impact of multiple variables on a wide range of cover crop N efficiencies and has served as a starting point for understanding the complex interactions of numerous variables (Table 3.5) on cover crop N efficiencies in the U.S. Coastal Plain Province. In the following paragraphs, I discuss the meaningful outcomes and offer explanations cited in the literature.

3.4.1 Test of the hypothesis

The data presented above support the original hypothesis that cover crop BMPs have an adequately tested basis for estimating their efficiency in the U.S. Coastal Plain Province. In my review of the cover crop literature, I identified 16 variations of N efficiency formulae used in calculating the 689 N efficiencies that widely range from 10 to 80%. The wide-ranging N efficiencies can be attributed to differences in spatial scale, cover crop species, modeling, and empirical methods combined with before-after and control-treatment experimental methods that evaluated the response of soil N, groundwater N export, and biomass above- and below-ground immobilization with and without cover crop growth during varying growing season lengths and over consecutive years of cover crop growth. The synthesis of factors influencing cover crop N efficiencies presented here provides a basis for better empirical and modeling studies in the future. I particularly suggest better and longer measurements and modeling of cover crop immobilization, soil N inventories, and groundwater N concentrations and export to improve our understanding of cover crops' role in reducing N losses from agricultural fields.

3.4.2 Influence of variables on cover crop nitrogen efficiencies

Four variables frequently appear in empirical and modeling BA and CT experiments: study length, cover crop species, spatial scale, and soil characteristics (Table 3.22). The mean N efficiencies of cover crop studies per method and experiment (n = 33, reference Tables 3.10 and 3.11) range from 7-86% and most N efficiencies were influenced by short-term study length, cereal rye cover crop, plot-scale cropland area, and well or moderately drained soils. More than half of the mean N efficiencies are greater than 50%. The N efficiencies greater than 65% are characterized by modeling or empirical methods using primarily CT groundwater N export or soil N experiments. These higher N efficiencies are achieved in less than 4y of consecutive cover crop growth and typically include cereal rye crops planted on plot-scale no-till croplands characterized as hydric soils that are well or moderately well-drained. Table 3.23 lists the significance levels between variable groups used in empirical and modeling cover crop N efficiency experimental approaches.

Table 3.22. Ranking mean cover crop N efficiencies in the U.S. Coastal Plain Province and common variables in the cover crop literature. The N efficiencies based on empirical and modeling before and after and control versus treatment experiments are influenced by variables frequently appearing in cover crop studies in the U.S. Coastal Plain Province. Abbreviations: “**Met**” = empirical (E) or modeling (M) approach followed by the experimental method, Before and After (BA) or Control versus Treatment (CT), “**Num**” = numerator of N efficiency formulae or N pathway such as December above ground biomass (D-AGB), December groundwater N flux w/ CC scenario (D-Gw), December soil N inventory (D-SI), December soil N flux w/ CC scenario (D-SN), N difference between Spring above ground biomass grown on soil residual N + 80 kg N and above ground biomass ground on soil residual N (S-AGB + N), Spring above + below ground biomass (S-ABGB), Spring above ground biomass (S-AGB), Spring direct pathways N flux w/ CC scenario (S-DP), Spring groundwater N export (S-Gw), Spring overland flow N flux w/ CC (S-O), Spring soil N flux w/ CC (S-SN), Spring soil N inventory (S-SI), “**Den**” = denominator of N efficiency formulae or N input such as Baseline December groundwater N flux w/o CC (D-Gw), Baseline December soil N flux w/o CC (D-SN), Baseline Spring direct pathways N flux w/o CC (S-DP), Baseline Spring groundwater N flux w/o CC (S-Gw), Baseline Spring soil N flux w/o CC (S-SN), Previous fall groundwater N export (F-Gw), Previous fall soil residual N (F-SN), Previous fall soil residual N + 80 kg N (F-SN + N), Previous spring cash crop fertilizer N (S-FN), Spring groundwater N flux w/o CC (S-Gw), Spring overland flow N flux w/o CC (S-O), Spring soil N flux w/o CC (S-SN), “**Reference**” reflects the paper reference identification code consisting of the publishing year and the first three letters of the first author’s last name as shown in Table 5, “**n**” = sample size, “**$\bar{x}$**” = the mean cover crop N efficiency as a percentage, “**se**” = the standard error, , “**Length**” = short term (ST, < 4 years) or long term (LT, ≥ 4y), “**Cover crop species**” refers to legumes Crimson clover (*Trifolium incarnatum* L.) (CC) and Hairy vetch (*Vicia villosa* Roth) (HV) and non-legumes Annual ryegrass (*Lolium multiflorum Lam*.) (AR), Barley (*Hordeum vulgare* L.) (B), Black oats (*Avena strigosa* L.) (BO), Cereal rye (*Secale cereale* L.) (CR), Cover crop mix includes a mixture of legume and non-legume or two or more non-legumes grown in one confined treatment area (M), Forage radish (FR, *Raphanus sativus*), Triticale (*Triticum secale* L.) (T), Winter wheat (*Triticum aestivum* L.) (W), “**Spatial scale**” = plot (Pl), field (F), SW (small watershed), or LW (large watershed), and “**Soil characteristics**” represents Hydric soils (Y) or non-Hydric soils (N), “HSG” = hydrologic soils group (HSG) such as well-drained (A), moderately well-drained (B), moderately poorly drained (C), and poorly drained (D), and “Tillage” represents the tillage type such as no-till (NT), low-till (LT), conventional-till (CV), Other tillage (Oth) which includes reduced-till, plowed seedbed, Average N efficiency based on NT and CT, and tillage type not reported in a study is denoted by “n/a”. The horizontal dash line marks the 50% N efficiency. Data sources: Tables 3.1, 3.6, 3.10, and 3.11.

Table 3.22. Ranking cover crop N efficiency mean groups in the U.S. Coastal Plain Province and common variables in the cover crop literature.

							Length		Cover crop species												Spatial scale				Soil characteristics						
									Legumes		Non-legumes														Hydric		HSG		Tillage		
Met	Num	Den	Reference	n	x̄	se	ST	LT	CC	HV	AR	B	BO	CR	M	FR	T	W	Pl	F	SW	LW	Y	N	AB	CD	NT	LT	CV
M-CT	S-SN	S-SN	2022GAI	11	86	5	x							x	x	x			x				x		x		x		
E-CT	S-SN	S-SN	1998STA	12	85	2		x						x						x				x	x	x	x		x
M-CT	S-Gw	S-Gw	2022GAI	11	82	6	x							x	x	x			x				x		x		x		
E-BA	S-SI	F-SN	2001COA	123	71	2	x					x		x			x	x	x				x	x	x		x		
M-CT	D-Gw	D-Gw	2022GAI	3	66	11	x							x	x	x			x				x		x		x		
M-CT	S-Gw	S-Gw	2020HIV	92	66	2		x				x		x				x				x	x			x	x		
E-BA	S-SI	F-SN	1997RAN	40	65	3	x																						
E-CT	S-Gw	S-Gw	2022SED	4	65	10		x							x					x				x		x			
E-CT	S-O	S-O	2020SMI	5	65	8	x		x	x				x	x				x				x		x		x		
E-CT	S-O	S-O	2018ARY	3	62	13	x					x		x				x	x					x	x				
E-CT	S-Gw	S-Gw	2017MEI	18	62	23	x						x					x		x			x			x			x
E-BA	S-AGB	S-FN	2005SAI	9	61	8		x		x				x	x				x					x	x		x	x	x
E-BA	D-SI	F-SN	1997RAN	13	58	5	x		x	x				x	x				x				x		x		x		
M-CT	D-SN	D-SN	2022GAI	3	55	19	x							x	x	x			x				x		x		x		
M-CT	S-Gw	S-Gw	2014YEO	12	54	6		x				x		x				x		x	x		x		x	x	x		
M-CT	S-DP	S-DP	2014YEO	6	52	9		x				x		x				x		x			x		x	x	x		
E-BA	S-AGB	F-SN	2007CLA	17	51	7	x			x				x					x				x		x				
E-BA	S-ABGB	S-FN	2005SAI	5	51	10		x		x				x	x				x					x	x			x	x
E-BA	S-AGB	F-SN	1992SHI	47	36	4	x		x	x	x			x					x				x		x		x		
E-BA	S-AGB	F-SN	2015KOM	36	34	2	x						x	x			x	x	x					x	x				
M-CT	S-Gw	S-Gw	2016LEE	12	33	3		x				x		x				x					x		x	x	x		
E-BA	S-AGB	S-FN	1997RAN	37	32	4	x		x	x				x	x				x				x		x		x		
E-BA	S-AGB	S-FN	1998RIT	9	31	10	x							x					x					x	x		x		x
E-BA	S-AGB	S-FN	1998STA	19	31	3		x						x					x	x				x	x	x	x		x
E-BA	S-AGB	S-FN	2007CLA	25	29	5	x			x				x					x				x		x				
E-CT	S-SN	S-SN	1998RIT	10	28	5	x							x					x					x	x		x		x
E-BA	S-AGB	S-FN	1992SHI	48	27	3	x		x	x	x			x					x				x		x		x		
E-CT	S-Gw	S-Gw	2018FIS	3	18	11	x					x			x			x		x				x	x				
E-CT	S-Gw	S-Gw	1998RIT	3	17	7	x							x					x					x	x		x		x
M-CT	S-DP	S-DP	2007SAD	15	16	3		x										x			x			x	x				
E-BA	D-AGB	S-FN	1998RIT	6	10	2		x						x						x				x	x	x	x		x
E-BA	S-Gw	F-Gw	1998STA	14	10	3	x							x					x					x	x		x		x
E-BA	D-AGB	S-FN	1997RAN	18	7	1	x		x	x				x	x				x				x		x		x		
						Count	22	11	6	10	2	7	2	28	12	4	2	10	24	6	3	1	18	15	29	9	18	6	10

Table 3.23. Summary of significant inputs and pathways influencing cover crop N efficiency. Abbreviations: “Var, Fig.” identifies the variable and figures, “Classification” lists variants, “Empirical (E)” and “p” denote empirical research methods and corresponding p-value of statistical tests, “Modeling (M)” and p denote modeling research methods and corresponding p-value of statistical tests. Data sources: Tables 3.7-3.9, 3.12-3.15.

Var, Fig.	Classification	Empirical (E)	p	Modeling (M)	p
Cover crop species,	Legumes	Non-leg (E) > Legume (E)	<0.0001	C. rye (M) > C. rye (E)	<0.001
	Non-legumes:	A. rye (E) = C. rye (E)	0.212		
	Annual ryegrass (A. rye)	Barley (E) > C. rye (E)	<0.001		
Figures: 7, 8, 9, 12, 13	Barley	Barley (E) > Barley (M)	0.1		
	Cereal rye (C. rye)	Wheat (E) > C. rye (E)	0.002		
	Wheat	Wheat (E) > Wheat (M)	0.004		
Experimental approach,	Before-after (BA)	Prev fall den (E) > Prev Sp den (E)	<0.001		
	Denominators (den):	Sp ABG num (E) = Sp AG num (E)	0.06		
	Previous fall soil residual N	Sp ABG (E) > December AG (E)	<0.001		
Figures: 5, 6, 7, 9, 10, 12, 13	Previous spring fertilizer N	Sp AG (E) > Dec AG (E)	<0.001		
	Numerators (num):				
	Spring above- and below ground (ABG)				
	Spring above-ground (AG)				
	December above-ground (AG)				
	Control-treatment (CT)			CT (M + E) > BA (E)	<0.001
N pathways,	Biomass immobilization (I)	I (E) > GW (E)	<0.001		
		Prev fall den (E, I)> Prev Sp den (E, I)	0.002		
Figures: 5, 6, 10, 11, 12	Groundwater N export (Gw)	Gw (E, CT) > Gw (E, BA)	<0.001	Gw (E+M, CT) > Gw (E, BA)	<0.001
				Gw (M, CT) > Gw (E, CT)	0.03
				GW (E+M, CT) > DP (M, CT)	<0.001
	Overland flow (O)	O (E, CT) > DP (E, CT)	<0.001		
	Soil N inventory (inv)	Soil N inv (E) > GW (E)	<0.001	Soil N (M, CT) > Soil N (E, CT)	0.04
		Sp Soil N inv (E) > I (E)	<0.001	Soil N (M, CT) > DP (M, CT)	<0.001
		Sp Soil N inv (E) > December soil N (E)	0.07		
	Direct pathways (DP)				
Study length,	Short-term	2y (E) > 1y (E)	0.001	2y (M) > 2y (E)	< 0.001
Figures: 7	Long-term	13y (E, I) > 9y (E, I)	0.046	10y (M, Gw) > 9y (E, I)	< 0.001
Temporal scale,	Publication year after 2006 (PY 2006)			PY 2006 (M) > PY 2006 (E)	<0.001
	Data collection year (Y)	1987-2002 (E) = 2012-2018 (E)	0.274		
Figures: 3, 4, 5, 9,12, 13	Growing days			Days and Y (M) > Days and Y (E)	<0.001

Table 3.23 (continued). Summary of significant inputs and outputs influencing estimates of cover crop N efficiency.

Var.	Classification	Empirical (E)	p	Modeling (M)	p
Soils	Hydric soils	N - Hydric (E) = Y - Hydric (E)	0.235	Y - Hydric (M) > Y - Hydric (E)	< 0.001
				Y - Hydric (M) > N - Hydric (M)	< 0.001
Figures: n/a					
	Hydrologic soil group:	A (E) > A (M)	< 0.001	B (M) > B (E)	< 0.001
	A, B, C, D, or any	B (E) > A (E)	0.014	B (M) > A (M)	< 0.001
	combination			B (M) > CD (M)	< 0.001
				CD (M) > A (M)	< 0.001
	Tillage type:	NT (E) > CT (E)	0.03	NT (M) > NT (E)	< 0.001
	No-till (NT)	NT (E) = LT (E)	0.09		
	Low-till (LT)	LT (E) > CT (E)	0.03		
	Conservation till (CT)				
Spatial scale	Plot	Plot (E) = Field (E)	0.17	Plot (M) > Plot (E)	< 0.001
		Plot (E) > Sm. wshd (M)	< 0.001		
Figures: n/a	Field	Field (E) > Sm. wshd (M)	0.01	Field (M) = Field (E)	0.13
				Field (M) > Sm. wshd (M)	< 0.001
	Lg. watershed (Lg. wshd)			Lg. wshd (M) > Sm. wshd (M)	< 0.001
	Sm. watershed (Lg. wshd)			Lg. wshd (M) = Field (M)	0.36
				Lg. wshd (M) > Plot (M)	< 0.0001
				Lg. wshd (M) > Field (E)	< 0.001
				Lg. wshd (M) > Plot (E)	< 0.001

3.4.3 Experimental approach: nitrogen pathways and nitrogen inputs

Empirical cover crop studies in the Coastal Plain Region have not demonstrated a consistent methodology to estimate N efficiency but instead adapt BMP efficiency equations 1 and 2 to the study methods and experimental approach. The historical record of cover crop studies documented the evolution of empirical approaches when the earliest cover crop studies estimated N efficiency by measuring N immobilized by the cover crop (Fig. 3.3). Recent empirical research, however, is more likely to measure N field losses directly and compare them to known quantities established by the amount of added fertilizer N during the prior spring cash crop planting.

Statistical tests indicated that cover crop N efficiencies based on empirical spring soil N inventories are significantly greater than N immobilization (<0.001, Fig. 3.12) and groundwater N export (<0.001). The results are consistent with the findings of Hirsh et al. (2021), where winter cereal or mix cover crops (winter cereal + crimson clover) reduced NO_3 in the upper 60 cm of soil by 67 % and 56 %, respectively. Representing cover crop N efficiencies via groundwater and soil N inventory experiments can produce high N efficiency outcomes; however, if cover crop N efficiencies are based on immobilization studies, N efficiencies will likely be lower than the former. These results, however, are inconsistent with the findings of Askar et al. (2023), who demonstrate that neither the use of cover crops, increasing liquid dairy manure application rate, or the combination of the two has a significant effect on mean monthly subsurface NO_3^--N loads. The findings by Askar et al. (2023) are based on empirical before-after-control-impact (BACI) methods applied on a flat (0-1% slope) silty clay loam soil (very poorly drained), requiring artificial drainage for crop production. The conflicting results mean agreement among researchers is needed to define cover crops' N efficiency in ways that do not limit or confound experimental results in multiple N loss pathways.

3.4.4 Data collection years and growing days effects on cover crop N efficiencies

Cover crop N efficiencies, both empirical and modeling, increased significantly by data collection year and growing days. There are few empirical N efficiencies after 2005 and few modeling studies before 2005; nonetheless, the data collection year is clearly a variable with a large impact on reported cover crop N efficiencies. The available data also show that reported modeling cover crop N efficiencies increased 1.5 times faster than empirical N efficiencies between the years of data collection, 1987- 2018 (Fig. 3.5). There were no significant differences detected between slopes of modeled and empirical cover crop N efficiencies during the growing season; however, modeled mean N efficiencies were significantly greater than empirical by a factor of 1.4 (Fig. 3.9). These results indicate models overestimate cover crop efficiency.

The strong increase in modeled cover crop N efficiencies has also been noted in the literature. Among conservation effects assessment (CEAP) watersheds, models overestimated the effectiveness of conservation practices (Osmond et al. 2012), and Moriasi et al. (2020) recently indicated that modeling CEAP data on conservation practice effects continued to be inadequate. In addition, in 1990, the Chesapeake Bay Program used model estimates of nutrient load reductions to report progress in water quality improvement. However, modeled reductions overestimated measured BMP efficiencies. The modeled BMP efficiencies were derived from “best professional judgment” and limited empirical research. BMP efficiencies were assigned using limited science from a controlled research site highly managed and maintained by an expert, and their operation and maintenance were deemed accurate. Consequently, the modeled

BMP efficiencies did not reflect the variability of empirical farming conditions (Simpson et al. 2009). This assessment of cover crop N efficiencies in the U.S. Coastal Plain Province shows that modeled cover crop N efficiencies are significantly higher than empirical cover crop N efficiencies, which indicates that progress towards improved water quality in the Chesapeake Bay and other regions will be overestimated by models using the modeled cover crop N efficiencies.

3.4.5 Modeled versus empirical cover crop nitrogen efficiencies

Many factors could have biased modeled cover crop N efficiencies reported in this research. Commonalities shared among reviewed modeling studies include the applied control-treatment approach, the watershed spatial scale, and the groundwater export and leachate N pathway. Additionally, a review of agricultural BMP effectiveness models conducted by Xie et al. (2015) indicates that modeling methods are spatially and temporally scale-dependent. The bay-level model uses coarse spatial data to determine load reduction goals, but Amin et al. (2020) suggest that finer-scale spatial data should replace coarse spatial resolution if regulatory plans are developed. Spatial data of higher resolution cannot consider the heterogeneity in local conditions, which affects BMP effectiveness (Amin et al. 2020). In the modeling studies assessed for my research, models utilize remotely sensed Landsat satellite imagery with a spatial resolution of 30 meters in watersheds no larger than 300 km^2. Considering the watershed area and imagery spatial resolution, there is potential for bias in the N efficiency because the spatial data may be too coarse to provide accurate cover crop N efficiencies that apply to smaller spatial scales (Dark et al. 2016). This means the basis of regulatory plans, such as the TMDL, should be finer-scale spatial data instead of coarse data.

Additionally, Liu et al. (2017b) indicate most BMP efficiency models assume constant nutrient removal performance based on expected maintenance and performance over the life of the BMP. For example, (Hively et al. 2020) modeled 10 years of consecutive cover crop applications, and results indicate N efficiency increased in subsequent years (Fig. 3.7a). However, as BMPs age, their nutrient removal capacity will likely change irrespective of maintenance because structures wear down and, in some cases, pollutants accumulate (Liu et al. 2017b). Although long-term empirical cover crop studies are limited, the results by Staver et al. (1998) demonstrated N efficiencies gradually declined each year after nine consecutive years of cover crop growth due to the depletion of soil N inventories and groundwater N concentrations (Fig. 3.7c). Liu et al. (2017b) also found that the water quality impacts of BMPs implemented at the watershed scale have not been as rapid or large as expected, possibly due to overly high expectations for the BMPs' long-term efficiency. My research also shows that in the case of annual BMPs like cover crops, the empirical mean N efficiency increases with plant maturation during a growing season. After 150 growing days, the mean N efficiency peaks at approximately 35% (Fig. 3.13). In contrast, the modeled cover crop N efficiency is nearly 60% (Fig 3.11b). This means models should reflect changes in BMP efficiencies over their lifetime.

3.4.6 Spring cover crop nitrogen efficiency

Cover crop N efficiency is strongly influenced by cover crop growing days (Baraibar et al. 2020). Empirical non-legume N efficiencies illustrated that N immobilization continues over 150 or more growing days (Fig. 3.13). In addition, interception via below-ground root biomass persists even though N in groundwater supply can fluctuate, and soil N inventories decline due to exhausting plant-available soil N (Fig. 3.9). After more than 150 growing days, empirical N efficiencies are higher because of mature plant tissue and root development (Meng et al. 2013) and (Paine et al. 2012). Figure 3.13 demonstrates how cereal rye N efficiency continued to increase after 150 growing days, and empirical soil N (Fig. 3.12) decreased as groundwater and immobilization (Fig. 3.11) increased N efficiencies during growing days 150-261 in spring. Because cover crops reach their maximum N efficiency during the spring, cover crops are woefully inadequate during the early stages of plant development. Therefore, additional BMPs should be implemented in the fall, or cover crops should be planted earlier to prevent N field losses (Komatsuzaki et al. 2015; Thapa et al. 2018; Baraibar et al. 2020; Sedghi et al. 2022). Producers should allow cover crops to grow beyond 150 days to achieve higher N efficiencies and, if possible, allow cover crops to grow beyond 170 days (Fig. 3.11) when mean efficiency exceeds 50% (Coale et al. 2001; Gaimaro et al. 2022). However, cover crops funded by cost-share programs require planting and terminating crops within a specified time window, preventing extended growing days (Gao et al. 2023).

3.4.7 Cover crop species

The cover crop N efficiency data explored here agree with the literature in that the N efficiency of non-legume cover crops is significantly higher than non-legume cover crops ($p < 0.0001$, Table 3.20) due to N fixation. Recent research efforts have explored cover crop mixes that include legume cover crops to reduce fertilizer applications and N leaching while increasing the N supply to cash crops (Thapa et al. 2018; Kaye et al. 2019). Thapa et al. (2018) found that nonleguminous cover crops reduced NO_3^- leaching by 56% over no cover crop controls. A literature review of cover crop applications in the United Kingdom conducted by (Kay et al. 2009) found cover crops lead to a 50% reduction compared to a winter-sown cereal. In my research of cover crop studies in the United States Coastal Plain province, the average nonleguminous cover crop efficiency was 51% ±1.5, which is within the range of cover crop N efficiencies reported by (Kay et al. 2009) and (Thapa et al. 2018).

One of the critical findings of my research is that the empirical mean N efficiencies of barley (69% ± 3.5, $p < 0.001$) and wheat (59% ± 4.1, $p = 0.002$) cover crops are significantly greater than the mean N efficiencies of empirical cereal rye (44% ± 2) (Table 3.20 and 3.23). These findings suggest wheat and barley cover crops should be planted instead of cereal rye cover crops. However, these findings conflict with well-established cover crop mean N efficiency values in the Coastal Plain province of the Chesapeake Bay watershed, where the traditional wheat cover crop N efficiency ranges from 11% to 31% and is lower than the traditional rye cover crop N efficiency range of 16 to 45% (CBP 2020a). The accepted higher N efficiency of rye cover crops is based on the empirical research conducted by Staver et al. (1998) and has since influenced the type of cover crop planted in the Coastal Plain province and other areas.

The disproportion between the mean N efficiency of wheat from the cover crop literature and the accepted standard used in the Chesapeake Bay watershed can be partially explained by the variables used to calculate wheat and cereal rye N efficiencies. On the one hand, winter wheat N efficiencies were based on observations of N pathways, such as soil N inventories and N immobilization, normalized by the previous fall soil residual N. On the other hand, cereal rye N efficiencies were based on N immobilization normalized by the previous spring fertilizer N. Comparison tests demonstrated that the N efficiencies for rye using the previous fall soil residual N as the denominator are significantly greater than the N efficiencies using the previous spring fertilizer N as the denominator ($p < 0.001$, Table 3.8 and 3.12). Additional tests revealed that the mean N efficiency based on the soil N inventory is significantly greater than immobilization ($p < 0.001$, Table 3.13). Figures 3.6, 3.10, and 3.13 show this pattern of influence on cover crop N efficiencies. Without standard practices in place to measure observed N loss and quantify N efficiency, inflated N efficiencies could overestimate anticipated water quality benefits.

3.4.8 Long-term studies

The relatively low number of long-term empirical cover crop studies hindered my ability to draw robust conclusions about improved cover crop N efficiencies over data collection years. However, the relatively long-term record of Staver et al. (1998) and the modeling study by Hively et al. (2020) provided an opportunity to examine N efficiency trends over time via N loss pathways and immobilization experiments (Fig. 3.7). During nine consecutive years of cereal rye growth, Staver et al. (1998) showed groundwater nitrate concentrations decreased by more than 60% in field-scale watersheds (~0.5 ha), which is consistent with the long-term, large watershed-scale (>200 km^2) modeling study by Hively et al. (2020). These authors demonstrated that the mean ± se cover crop N efficiencies over ten modeled years were 66 ± 1.9 %, similar to the empirical value reported by (Staver et al. 1998). Additional long-term, empirical studies with cover crops are needed to corroborate the recent modeling of Hively et al. (2020). The N efficiencies measured or assumed in these long-term studies are likely related to the depletion of soil N inventories and groundwater N concentrations similar to decreases shown empirically by (Bunnell-Young et al. 2017) when agricultural fertilization ceases.

3.4.9 Short-term studies

Of the 583 N efficiencies displaying significant levels associated with study length, 77% were based on short-term studies of 3 years or less (Table 3.19), which is consistent with Liu et al. (2017b), where the results indicate that most empirical studies have focused on short-term efficiencies, while few have explored long-term efficiencies. N efficiencies can vary widely among short-term empirical studies that are 1 – 3 years long. For example, studies have observed cover crops planted between September and mid-October and harvested in December experience a short growth period. N efficiencies based on December biomass would be expected to be less than N efficiencies based on samples taken the following spring (< 0 .001, Table 3.14, Fig. 3.6). However, Gaimaro et al. (2022) demonstrated N efficiencies could be high in December if based on modeled control-treatment groundwater export (40%) or soil N inventory (20-90%) experiments (Figs. 3.11 and 3.12). Ranells et al. (1997) conducted empirical soil N inventory experiments in December after 69 growing days. Findings consisted of variable N efficiencies from 37-86% (cereal rye n = 4), 55-77% (Rye/legume mix n = 4), and 20-72% (legume n = 5). Studies of 1-3 years showed that consecutive years of cover crop planting increased the N efficiency over time. For example, after two successive years of planting rye cover crops, Ranells et al. (1997) showed that the average N efficiency immobilized by cover crops increased from 6% to 35% during the second year. Staver et al. (1998) demonstrated that under ideal conditions, rye cover crops planted early and drilled into the soil could utilize up to 45% of the unharvested N (See Table 3.10 and 3.11 for descriptive statistics per study classified by experimental approach). These short-term studies demonstrate relatively high efficiencies within a few years of successive cover crop planting.

The number of short-term studies demonstrating variable N efficiency partially explains the appearance of empirical N efficiencies having unchanged before and after 2006. Depicting short-term studies at the temporal scale of data collection years can demonstrate preferential experimental methods to measure N, such as via N immobilization, groundwater N export, or soil N inventory, but this can mislead the user who hopes to consistently achieve high cover crop N efficiencies after four or more successive years of cover crop use. Better and user-friendly long-term cover crop success measures are post-harvest surface soil N concentrations and groundwater nitrate concentrations. Depicting short-term cover crop studies separately from long-term studies using the data collection years time scale could improve our understanding of cover crop N efficiencies over data collection years.

3.4.10 Soil characterization

Tillage

In this assessment, cover crop N efficiencies on low-till and no-till fields were not significantly different. Mean group tests showed that empirical cover crop N efficiencies were higher under low and no-tillage practices than empirical conventional till fields (Table 3.9). The cover crop N efficiencies based on tillage types are in relative agreement with the reported N efficiencies assigned to N efficiencies associated with conservation tillage BMPs (Hanson 2018). One notable exception in this assessment found that modeled cover crop N efficiencies based on no-till were significantly greater than empirical cover crop N efficiencies under no-till, and this indicates that future modeled cover crop N efficiencies with no-till should also be more conservative (Table 3.9). Cover cropping combined with no-till or reduced tillage improved soil health conditions more than each one alone as individual BMPs (Farmaha et al. 2022).

Soil drainage class

Except for the empirical control-treatment overland flow study by (Aryal et al. 2018), all empirical studies took place entirely or partially on well-drained or moderately well-drained soils. There was insufficient data to evaluate empirical N efficiencies on poorly drained soils. Modeling studies, however, indicated that N efficiencies based on poorly drained soils are significantly greater than those based on well-drained soils (Table 3.9). Additionally, the results of a meta-analysis of nonleguminous cover crop efficiencies by Thapa et al. (2018) confirm nonlegumes reduced nitrate leaching more effectively on coarse−textured soils and in drier years.

Hydric and non-hydric soils

Based on the literature reviewed, no detectable differences were found between empirical N efficiencies based on hydric and non-hydric croplands (Table 3.9). However, modeled studies demonstrate a clearly significant difference between higher N efficiencies based on hydric soils and those attributed to non-hydric soils. Yeo et al. (2014), Hively et al. (2020), and Gaimaro et al. (2022) modeled N efficiencies associated with hydric soils and showed that N efficiencies are significantly greater than empirical ones based on hydric soils. The models suggested that N efficiencies on hydric soils are significantly greater than those based on non-hydric soils (Table 3.9). Validating these findings of modeling studies, Koskelo et al. (2018) showed in an empirical study that most N export occurred during baseflow and that during a storm event, watershed topography, not hydric soils, controlled storm discharge. Surface ponding of water on hydric soils intercepted overland flow, reducing the impacts of low infiltration rates. Additional empirical cover crop studies applied to hydric and non-hydric soils are needed to substantiate N efficiency differences between non-hydric and hydric croplands.

3.4.11 Spatial scale of empirical and modeling experiments

Another disparity shown in this review of cover crop studies relates to the effects of spatial scales on N efficiency. Modeling scenarios are primarily based on larger geographic scales from plot-scale upwards to 300 km^2, whereas empirical studies were applied mainly to croplands smaller than 20 ha. This finding is consistent with the results of Kay et al. (2009), whose review of studies focused on agricultural stewardship measures in the United Kingdom were all applied on the plot and field scale. In addition, this assessment found that the N efficiencies based on the earliest empirical studies relied on before-after experiments applied to N immobilization, soil N inventories, and groundwater export at spatial scales of <0.5 ha (termed "field-scale watershed" by Staver et al. 1998). The mean N efficiencies calculated from data produced by the earliest empirical studies (n = 509, 46% ± 1.3) are not significantly different than recent empirical studies (n = 15, 55% ± 6.7) by Aryal et al. (2018) and Fisher et al. (2018), who applied control-treatment groundwater experiments to field-scale croplands (Table 3.8 and 3.17). The cover crop literature emphasizes the need for empirical research at a larger spatial scale (Mulla et al. 2005; Kay et al. 2009; Simpson et al. 2009). However, watershed-scale studies are difficult due to cooperation from all farmers, coordinating management practices, long-term commitment from researchers, and costs. As a result, estimates of cover crop N efficiency at the watershed scale are subject to high uncertainty (NRC 2011). Simpson et al. (2009) suggested examining spatial and temporal variables to minimize uncertainty in BMP efficiencies by adjusting efficiencies estimated from small research plots to larger spatial areas.

In recent research, modeling studies and empirical studies provided conflicting results. Modeled BMP efficiencies were only detectable at the larger watershed level (Giri et al. 2020). In contrast, a recent field study of 166 small artificial drainage basins in the Florida Everglades, USA, revealed that BMP impacts were only detectable at the smaller farm scale (Yoder et al. 2020). Modeled N efficiencies (n = 165) drawn from CT scenarios applied to variable spatial scales upwards of 300 km^2 were significantly greater than empirical N efficiencies ($n = 524$, $p < 0.001$). This assessment showed that the recent field-scale empirical CT cover crop N efficiencies (2012-2018) are statistically similar to the earlier plot- and field-scale empirical BA and CT cover crop N efficiencies (1987-2002). More empirical field-scaled research is needed to study the long-term effects of cover crops and empirical results can be used to validate field-scale models. The collective modeling of field- scale cover crop implementation could help improve our understanding of cover crops in a watershed (Table 3.7).

3.4.12 Cover crop efficiency uncertainties

The agricultural BMP literature reported wide variability in N and P efficiencies at the national, regional, and watershed levels. There is a degree of uncertainty in these efficiency estimates at these different scales. For example, over 200 BMPs were accredited in the Phase 6 Chesapeake Bay watershed Model (CBWM), and many agricultural BMP efficiencies remained unchanged from previous phases (Pickford 2022). However, some BMPs, such as cover crops, have numerous variants for different cover crop plant types, planting dates, and whether the cover crop is harvested, plowed in, or left as a protective cover on the field. Each cover crop variant could affect the overall modeled cover crop efficiency. The BMP efficiencies are a critical component of both water quality goal-setting and tracking BMP implementation progress in the CBWM, but uncertainties in BMP efficiency can lead to overly optimistic model expectations (NRC 2011; Stephenson et al. 2018).

Study comparisons give us our first clue about what could influence cover crop N efficiency. Often, model comparisons to empirical research are necessary to validate modeling study outcomes. Important findings of this research include model N efficiencies were significantly higher than empirical studies and model N efficiencies increased over consecutive years of cover crop planting. These modeled N efficiencies could bias water quality studies in the U.S. Coastal Plain, and lead to overly optimistic nutrient reductions and water quality improvements. Model projections and on-the-ground validations are needed to minimize uncertainty in model predictions.

Uncertainty surrounding cover crop efficiencies has not slowed the use of cover crop BMPs by farmers across the U.S. and Europe, probably because farmers have recognized that cover crops can counter eutrophication and provide additional benefits to soils and future crops (Kaye et al. 2019; Farzadfar et al. 2021; Wallander et al. 2021; Rivière et al. 2022). For example, (Storr et al. 2019) indicates applications of cover crops are growing in the United Kingdom because of the benefits to soil structure, soil erosion control, and water infiltration, and the reductions in using chemical fertilizers, herbicide, and fuel. Although the literature showed cover crop N efficiencies vary widely, which raises questions regarding their contribution to water quality improvement, program managers should continue to promote the co-benefits of planting cover crops to ensure farmers grow more cover crops.

3.4.13 Climate change affects management efficiencies

The N and P reduction goals needed to achieve water quality and the BMP efficiencies measurement of pollutant removal performance are generally based on historical climate (Schmidt et al. 2019). However, anthropogenic climate change has likely contributed to increased global average precipitation over land since 1950, with a faster rate of increase since the 1980s (Masson-Delmotte 2021). Changes in precipitation are expected to increase riverine TN within the continental United States (Renkenberger et al. 2017; Sinha et al. 2017). In a more recent study, Ator et al. (2022) show a slight net decline in annual N export to the Chesapeake Bay between 1995 and 2025 due to increasing rates of denitrification, ammonia volatilization, and changes in plant phenology that offset a wetter climate. However, local field measurements of N export from bay tributaries draining the Delmarva Peninsula show increasing TN and phosphate (Fisher et al. 2021). Schmidt et al. (2019) and Giri et al. (2020) predict a rise in streamflow and surface runoff and increases in agricultural source loads of sediment, nitrogen, and phosphorous under future increases in temperature and precipitation. Moreover, most BMPs continue to reduce nutrient export, but BMP removal efficiencies decline due to more intense runoff events, biological responses to changes in soil moisture and temperature, and intensified upland nutrient losses (Schmidt et al. 2019). A global review of cover crop efficiencies by Thapa et al. (2018) confirms nonleguminous cover crops effectively reduce NO_3^- leaching, improving water quality. Still, cover crop N efficiency is partially influenced by precipitation (Staver et al. 1998; Thapa et al. 2018). Renkenberger et al. (2017) modeling results suggest that in the U.S. Northeast, BMPs designed to remediate water quality problems under the current climate will be insufficient to maintain water quality with climate change. BMP climate change adaptations, such as sizing and materials, will require more applications that are much more widespread within watersheds, and in some cases, program managers will need to redesign existing BMPs to adapt to climate change impacts.

3.5 Agronomic recommendations

- Plant fall cover crops as early as possible and supplement cover crops with other BMPs to increase N interception when cover crops are least efficient in the fall.
- Increase the number of cover crop growing days to increase the cover crop N efficiency.

3.6 Research recommendations

- The basis of cover crop N removal capabilities should be the N accumulation within the above-ground and below-ground biomass normalized by the fall soil residual N measured after harvest in long-term empirical studies.
- Establish a standard for reporting cover crop N efficiency that includes inputs, pathways, and date of measurements.
- Continue to apply multiple experimental approaches to identify N loss pathways needing additional BMPs where and when cover crops are insufficient to control N losses.
- The basis of regulatory plans, such as the TMDL, should be finer-scale spatial data instead of coarse data.
- There is a need for more empirical studies to help future models incorporate the removal processes of soil and groundwater N.
- Models should reflect changes in BMP efficiencies over their lifetime.
- Funding agencies should increase the number and duration of long-term empirical and modeling studies to quantify cover crop N efficiency at plot, field, and watershed scales.

Chapter 4: Measured and modeled nitrogen and phosphorus concentrations and yields after more than 30 years of implementing agricultural best management practices in the Greensboro watershed

Abstract

Water quality is decreasing as BMPs have significantly increased in the Greensboro watershed. To understand why, I assessed the influence of progress years (July to June), annual discharge totals, agricultural land-based BMPs, and animal waste management BMPs on nutrient concentration and yields derived by two USGS approaches and CAST-modeling. The main hypothesis of Chapter 4 is that the three methods of estimating N and P concentrations and yields are in agreement and show a relationship to BMP implementation in the Greensboro watershed. To test this hypothesis, I compiled annual nutrient (N and P) datasets based on (1) USGS field measurements of concentrations and discharge, (2) USGS flow-normalized weighted regression based on time, discharge, and season (WRTDS) of concentrations and yields, and (3) CAST-modeled nutrient yields. Statistical analyses revealed the influence of time, discharge, agricultural BMPs, and animal waste management BMPs on the three methods. Results indicated that the USGS field measurements and WRTDS flow-normalization methods consistently showed an increase in N and P concentrations and yields. In contrast, all CAST-modeled regressions showed significantly decreasing nutrient concentrations and yields ($p \leq 0.05$), which did not support the hypothesis that all three methods are in agreement. Despite CAST-modeled results decreasing with increasing BMP implementation, which supports the hypothesis that N and P concentrations and yields show a relationship with BMP implementation, USGS methods resulted in increasing nutrient concentrations and trends. The long history of manure applications on cropland, partially to grow animal feed that supports the poultry industry, is a major reason

for increasing N export via groundwater and soil-P saturation in the Greensboro watershed. The increase in animal waste management BMPs and simultaneous annual manure applications suggest significant underestimates of CAST-modeled N and P export due to overestimated BMP efficiencies. Increasing N and P exports based on USGS methods suggests insufficient BMPs to offset the annual nutrient inputs or nutrient inputs overwhelm adequate amounts of functioning agricultural BMPs. I recommend using adjusted BMP efficiencies during cultural and structural BMP lifespans to improve model outputs. I also suggest two approaches to reflect the role of annual poultry manure applications: (1) model nutrient transport via artificial drainage ditches that interfere with natural nutrient flow pathways and exacerbate N and P transport, and (2) model the accumulation of soil-P and saturated soil-P, resulting in increases in dissolved P and particulate P in downstream surface waters. Agronomic recommendations include developing efficient manure recycling approaches within the local agricultural systems via nutrient management practices and concurrent research and development to support alternative uses of animal waste, including composting, bioenergy generation, granulating/pelletizing, and establishing a marketplace to support the sale of these products and to offset the costs of transporting manure from areas of manure surplus to manure deficit areas.

4.1 Introduction

4.1.1 Measured and modeled water quality response with management practices

A disconnect exists between modeling water quality response based on the reported implementation of best management practices (BMPs) and the field measurements of water quality response to on-the-ground BMP implementation. For example, watershed-scale models can assess the effectiveness of best management practices and predict the water quality response to management improvements (Xie et al. 2015; Miller et al. 2019). The modeled water quality responses in the Chesapeake Bay watershed and Great Lakes basin in the United States and Xiangxi River watershed in China demonstrate changes in land management can control nutrient runoff (Roberts et al. 2009; Meixler et al. 2010; Roberts et al. 2010; Liu et al. 2013; Abouali et al. 2017). Furthermore, federal and state funding in the United States has increased participation and widespread BMP applications in the Chesapeake Bay watershed (Silaphone, Dissertation Chapter 2) despite incomplete data on the non-funded, voluntary implementation of best management practices (Fanelli et al. 2019; Harding et al. 2019; Sekellick et al. 2019; Ator et al. 2020; Hively et al. 2020). The modeling results by Roberts et al. (2009) and Miller et al. (2019) show that if enough BMPs are installed and maintained, then the cumulative effect of BMP implementation should decrease watershed nutrient export concurrent with a growing population, increased development, and more intensive agricultural land uses.

Similarly, empirical studies have demonstrated that agricultural BMPs can reduce nutrient export from croplands at small spatial scales (Shipley et al. 1992; Staver et al. 1998; Christianson et al. 2017a; Rosen et al. 2017; Hirsh et al. 2021; Lucas et al. 2021). In contrast, (Fisher et al. 2021) show improvements in the Choptank River had little to do with agricultural best management practices. Instead, improvements to point sources, such as upgrading wastewater treatment plants, demonstrably reduced nutrient export to the bay tributaries (USEPA 2015; Liner et al. 2017; Ator et al. 2019; Oelsner et al. 2019; Fisher et al. 2021), and the enforcement of the 1990 Clean Air Act reduced nitrate-N in the Upper Potomac River (Eshleman et al. 2013; Eshleman et al. 2016) and contributed to 20% reductions in direct atmospheric deposition in the Choptank River basin (Fisher et al. 2021). Overall, model estimates of atmospheric N inputs to the Chesapeake Bay tributaries declined by 25% between 1992 and 2012 (Ator et al. 2019). Fanelli et al. (2019), Ator et al. (2020), and Fox et al. (2021) show attempts to reduce agricultural and urban non-point source (NPS) pollution have yielded mixed results.

Much of the disconnect between BMP implementation and empirical measurements of nutrient export from watersheds is attributed to long groundwater travel times (Sanford et al. 2013; Hill 2019; Lintern et al. 2020). The extent of time lags in Europe and North America are influenced by climate, landscape, and management scenarios and are considered at the policy level when establishing realistic deadlines and expectations and conveyed to stakeholders interested in measured nutrient reductions following BMP implementation (Collins et al. 2008; Vero et al. 2017). For example, Jiang et al. (2017) attribute the delayed responses of groundwater quality to field management adjustments to the uniform flow-dominated vadose zone in agricultural landscapes in Prince Edward Island in Canada between 2011 and 2016. The variable groundwater residence times within the Coastal Plain aquifers in the United States indicate that measuring the effect of BMP implementation on nonpoint source N groundwater discharge may result in undetectable changes in stream water quality (Staver et al. 1998). Depending on the orientation and length of groundwater flow paths, 1-2 decades may pass in Delmarva before the BMP effects are measurable in surface water quality (Lindsey et al. 2003; Ator et al. 2015), which is consistent with the findings of Sebilo et al. (2013) and Sanford et al. (2013). Sutton et al. (2009) detected a 28% decrease in baseflow P concentrations a decade after BMP implementation in the German Branch sub-basin in the northwestern portion of the Tuckahoe Creek watershed. Staver et al. (1998) measured an overall reduction in NO_3^- concentration while using rye cover crops for nine consecutive years from 1988 to 1995. In contrast, there have been documented reductions in local groundwater nitrate concentrations (90% in 3-5 years) resulting from converting agricultural land to conservation practices (Bunnell-Young et al. 2017). Additionally, Lebo et al. (2012) evaluated flow-normalized nutrient export trends in the Neuse River basin from 1984 to 2009 and found decreasing NO_3-N concentrations in parallel with increasing efforts to achieve the Neuse River TDML. Given the 13 years since the Chesapeake Bay TMDL, stream baseflow concentrations should exhibit decreasing nitrate concentrations if sufficient BMP interception occurs (Fox et al. 2021).

4.1.2 Long-term monitoring in a small rural watershed

Decades of management efforts in the Chesapeake Bay watershed have resulted in measurable improvements in water quality where point sources and atmospheric nitrogen sources were reduced (Eshleman et al. 2016; Ator et al. 2020; Fisher et al. 2021). Conversely, water quality largely influenced by nonpoint sources has not improved water quality. An early study by Ritter et al. (1984) initially raised concerns about increasing nutrients in groundwater where 8% of wells in Kent County, Delaware, and 21% - 32% of wells in Sussex County, Delaware, had average nitrate (NO_3) concentrations above the EPA drinking-water standard of 10 mg N L^{-1}. The applications of poultry manure and fertilizer and failing septic tanks contributed to the high NO_3 concentrations in groundwater. In contrast, NO_3 concentrations in forests were <1.5 mg L^{-1} (Ritter et al. 1984). A recent study by Ator et al. (2020) shows that flow-normalized nitrogen and phosphorus fluxes have increased for several decades at the USGS gauge at Greensboro in the Choptank River basin. Moreover, an application of linear regression (Fig. 1.3) by Fisher et al. (2021) also found that the USGS long-term water quality record indicates an overall increase in TN and TP. The increasing TN and TP in the surface waters of the nontidal portion of the Choptank River gives more reason for concern as nutrient levels are approaching the nutrient criteria of 2.5 mg TN L^{-1} and currently exceed the nutrient criteria of 0.094 mg TP L^{-1} for healthy streams in Maryland (Morgan et al. 2013). In addition, two-thirds of the Choptank River headwaters lie in Delaware, and the Delaware nutrient threshold values, 3.0 mg TN L^{-1} and 0.2 mg P L^{-1}, are also frequently exceeded (DNREC 2005).

Water quality is degrading in the Greensboro watershed (Hirsch et al. 2010; Langland et al. 2012; Zhang et al. 2015a; Ator et al. 2020). The long-term water-quality record at the Greensboro gauge also shows brief periods of interannual variability in N and P concentrations. Detectable fluctuations in nutrient concentration may indicate a possibility of events, or a singular event, that may have influenced water quality. For example, after the enactment of the Maryland phosphate detergent ban in December 1985(Jones et al. 1986; Boesch 2001; Ernst 2003), Jones et al. (1986) measured reductions in P concentrations from wastewater treatment plants in Maryland and the USEPA (1997) found that annual point source P export to the Chesapeake Bay declined from 5,100 metric tons in 1985 to 2,500 metric tons in 1996. Similar phosphate bans in North Carolina resulted in improvements when wastewater P removal upgrades and a P-detergent ban in the late 1980s decreased P loading to the nutrient-over-enriched Neuse River Estuary in North Carolina (Paerl et al. 2004).

4.1.3 Offset nutrient removal benefits of management practices

Modeling and empirical BMP studies have demonstrated that BMPs can effectively reduce nutrient export; still, the Bay states are at risk of not having enough documented improvements in water quality, making the Bay TMDL goals challenging to meet by 2025 (Surrick 2022). Factors contributing to undetected improvements in water quality or, in some cases, elevated nutrient concentrations include hydrogeology, soil types, BMP effectiveness and maintenance, and climate change (Lintern et al. 2018; Harding et al. 2019; Ator et al. 2022). For example, combining local hydrogeology and soil types on the Delmarva Peninsula can efficiently move nutrients from the landscape to local streams while supporting intensive agriculture. Much of the Choptank River basin is characterized by sandy and permeable soils, which provide better drainage and require less ditching to drain relatively flat croplands (Staver et al. 1995; Ator et al. 2015). A flat topography encourages the slow movement of groundwater through a hypoxic environment more suitable for denitrification (Staver et al. 1998). Where anoxic conditions exist, complete denitrification is more likely to remove NO_3^- from groundwater via N_2 gas (DNREC 2005; Ator et al. 2015). Additionally, NO_3^- concentrations in small streams draining forested areas having predominantly poorly drained soils are less than 0.5 mg L^{-1} (McCarty et al. 2008; Denver et al. 2014). However, in the Tuckahoe Creek, located in the western part of the Choptank River basin, the NO_3^- concentration in well-drained agricultural areas during baseflow is often 5-10 mg N L^{-1}, higher than poorly drained nontidal areas (2-5 mg N L^{-1}) farther east (McCarty et al. 2008; Ator et al. 2015).

A BMP correctly installed and maintained over its lifetime can reduce field losses (Lowrance et al. 1997; Messer et al. 2017). However, anthropogenic changes to the landscape, natural conditions of the terrestrial landscape, and the orientation of groundwater flow paths can offset BMP effectiveness. For example, ~67% of the degraded stream miles in the Upper Choptank River watershed are channelized to drain hydric soils for agriculture. As a result, agriculture is the dominant land cover and land use in the Choptank River basin (Benitez et al. 2004), and studies have shown that artificial drainage ditches alter natural nutrient flow paths and exacerbate N and P groundwater transport to downstream surface waters (Needelman et al. 2007; Vaughan et al. 2007; Carstensen et al. 2020). Groundwater supplies the majority of NO_3^- to streams in the Choptank River basin (Koskelo et al. 2018), and NO_3^- concentrations in individual streams reflect concentrations in local contributing groundwater (Staver et al. 1998; Knee et al. 2013; Ator et al. 2015). However, groundwater carrying NO_3^- may pass far beneath the root zone of cover crops and natural vegetation, reducing interception of nutrients, and oxic conditions ensure the persistence of NO_3^- (Ator et al. 2015).

Some agricultural BMPs do not reduce nutrients but move nutrients from one location to another for cropland applications. For example, animal waste management practices are BMPs that promote the safe storage of manure until environmental conditions are suitable for manure application onto cropland or pasture (Mukhtar 2005; Hawkins et al. 2016). Manure incorporation and injection are BMPs that aim to lower ammonia-N volatilization and can lower dissolved P and N losses via overland flow. Manure incorporation requires mixing manure into the soil in 1 to 3 days, whereas manure injection requires mixing manure into the soil profile within 24 hours (Dell et al. 2016). However, in areas of intensive livestock production, manure surplus exceeds the assimilative capacity of limited croplands to receive manure applications, resulting in N and P leaching and overland flow (Petersen et al. 2007; Kellogg et al. 2014).

4.1.4 Research purpose

Water quality is decreasing as BMPs have significantly increased in the Greensboro watershed (e.g., Fox et al. (2021)). Thus, I assessed progress years, annual discharge totals, agricultural land-based BMPs, and animal waste management BMPs with nutrient export to understand why. The main hypothesis of Chapter 4 is that three methods of estimating N and P concentrations and yields are in agreement and show a relationship to BMP implementation in the Greensboro watershed. To test this hypothesis, I compiled annual nutrient (N and P) datasets based on (1) USGS field measurements of concentrations and discharge, (2) USGS flow-normalized weighted regression based on time, discharge, and season (WRTDS) of concentrations and yields, and (3) CAST-modeled nutrient yields. Major research questions addressed in Chapter 4 are:

1. Have BMPs influenced nutrient concentrations and yields in the Greensboro watershed?
2. Besides BMP implementation, have other factors influenced nutrient concentrations and yields in the Greensboro watershed?

4.2 Methods

Agricultural factors were considered to evaluate long-term TN and TP export from the Greensboro watershed with changes in the surface water quality during the progress years (July 1 to June 30). The data are aggregated by progress years because these intervals only report CAST modeling data and results. The data obtained for this analysis are publicly available datasets from the USGS National Water Information System water-quality database (https://nwis.waterdata.usgs.gov/md/nwis/qwdata), Chesapeake Assessment Scenario Tool (CAST) (http://cast.chesapeakebay.net/), and the National Centers for Environmental Information (NCEI) National Oceanic and Atmospheric Administration (NOAA) (https://www.ncei.noaa.gov). These data are summarized in Table 4.1 and further explained in the subsequent sections.

4.2.1 Study site

This analysis focuses on the Greensboro watershed on the Delmarva Peninsula, which is described in the Chapter 3 methods section (Fig. 3.1). The Greensboro watershed is located at the intersection of three counties and two states: Caroline and Queen Anne's counties in Maryland and Kent County, Delaware. The data utilized here were initially aggregated at the watershed or county scales (Table 4.1). The drainage area reported by the USGS is 293 km^2; however, the area of the Greensboro watershed land-river segment used in the Chesapeake Assessment Scenario Tool (CAST) is 303.29 km^2. The small difference is primarily due to additional land area to the north, southwest, and southeast. The drainage area and land-river segment area influenced yield calculations.

Table 4.1. Summary of data requirements. Abbreviations: "Data Type" classifies datasets into four types: drainage area, hydrology, influential factors, and surface water quality. "Scale" describes the spatial scale of the original data set where RDA is the USGS reported drainage area, LRS is the Greensboro watershed land-river segment, and Tri-county represents Kent County, Delaware, and Maryland counties, Caroline and Queen Anne's. "File/Report" defines each tabular file obtained from NOAA or USGS. The definition of each CAST report type is available in Documentation Results at https://cast.chesapeakebay.net/Documentation. "Data Source" represents the data provider, where CAST means the Chesapeake Assessment Scenario Tool web interface.

Data Type	**Description**	**Scale**	**File/Report**	**Data Source**
Drainage area				
	USGS reported drainage area (RDA): 293 km^2	RDA	n/a	USGS station 01491000
	CAST land-river segment (LRS): 304 km^2	LRS	Land-river segment GIS file	CAST
Hydrology				
	Precipitation observations	Dover, DE	Daily summaries	NOAA station USC00072730
	Daily discharge observations Parameter code: 00060	RDA	Daily discharge	USGS station 01491000
	Reported monthly average discharge Parameter code: 00060	RDA	RIM_2022_Monthly LoadTable.xlsx	Mason et al. 2023
Agricultural factors				
	Crop N and P needs	Tri-county	Nutrients Applied	CAST
	Land-based Agricultural BMPs	LRS	Land BMPs	CAST
	Animal waste management BMP	LRS	Animal BMPs	CAST
	N and P inputs via Livestock and poultry manure, Fertilizer, Biosolids, and Direct deposition onto pasture	Tri-county	Nutrients Applied	CAST
	Stored poultry manure N and P	Tri-county	Manure Nutrients Applied	CAST
Surface water quality				
	Field/lab measurements Parameter codes: 00600 (TN), 00665 (TP)	RDA	Monthly measurements	USGS station 01491000
	Weighted regression based on time, discharge, and season (WRTDS) flow-normalization Parameter codes: 00600 (TN), 00665 (TP)	RDA	RIM_2022_Monthly LoadTable.xlsx	Mason et al. 2023
	CAST-modeled Edge of tide (EOT) TN and TP	LRS	Loads per unit	CAST

4.2.2 Annual precipitation

Daily precipitation measurements (mm) applied to the Greensboro watershed were obtained from the nearest Global Historical Climatology Network daily (GHCNd) summaries station in Dover, Delaware. The GHCNd is an integrated database of daily climate summaries from land surface stations across the globe and is comprised of integrated daily climate records subjected to consistent quality assurance reviews. The Dover, Delaware NOAA station ID #USC00072730 lies 12 km east of the Greensboro watershed in Kent County (Lat: 39.1467°, Long: -75.5055°, 9.1 meters asl, Fig. 3.1). The long-term historical record dates back to 1893 and is publicly accessible at the National Centers for Environmental Information (NCEI) National Oceanic and Atmospheric Administration (NOAA) (https://www.ncei.noaa.gov) website. The annual precipitation (mm y^{-1}) record between 1970 and 2021 is the sum of the multiday and daily precipitation observations per progress year.

4.2.3 USGS data: field measurements, flow-normalization, discharge

The USGS gauging station (01491000) at the Choptank River near Greensboro, Maryland is in Caroline County, Maryland (Lat. 38°59'49.9", Long. 75°47'08.9"), 0.032 km upstream of Gravelly Branch and is 0.83 m asl (Fig. 3.1). Station 01491000 at the Choptank River is the only River Input Monitoring (RIM) station located on the Delmarva Peninsula and is described in Chapter 3 methods. The gauge has monitored the nontidal portion of the Choptank River, reportedly a drainage area of 293 km^2, for hydrology since 1948 and for water quality since 1965. At this site, a dam separates the nontidal portion of the Choptank River from the tidal portion.

USGS TN and TP export measurements and daily discharge

Daily discharge (cfs) and field/lab measurements of TN and TP concentration (mg L^{-1}) in surface water are publicly available at https://waterdata.usgs.gov and from the USGS National Water Information System water-quality database (NWIS) Web database at https://nwis.waterdata.usgs.gov/md/nwis/qwdata, respectively. Here, I report the annual discharge (m^3 y^{-1}), the sum of the reported daily discharge measurements per progress year between 1970 and 2021. The sampling frequency of surface water occurred once or twice per month, and I combined monthly water chemistry and discharge to estimate the monthly export of N and P (kg $month^{-1}$). The monthly export was then summed to calculate annual TN (1975 to 2021) and TP (1970 to 2021) export per progress year. Annual export of N and P was converted to annual N and P watershed yields (kg N or P ha^{-1} y^{-1}) based on the USGS-reported drainage area (293 km^2). The annual discharge and water quality measurements included all approved and provisional data, which may change after the data retrieval date 2023 September 18.

USGS WRTDS flow-normalized monthly TN and TP export and mean discharge

The total mass of N and P export and changes in export in major rivers across the Chesapeake Bay watershed have been calculated using monitoring data from the Chesapeake Bay RIM Network stations from 1985 through 2022. Nutrient export and changes in export were determined by applying a weighted regression approach called WRTDS (Weighted Regression on Time, Discharge, and Season), described by Hirsch et al. (2010), to the analysis of long-term surface water quality data. Hirsch et al. (2010) also described the “flow-normalization” procedure applied to WRTDS to ensure that emerging trends are a result of the change in the way the Greensboro watershed responds to the full range of hydrologic conditions and not a short-term temporal pattern of discharge during the sampling period. Flow normalized concentrations and flux were computed by estimating an expected concentration for each day of the record using the observed daily discharge. By using the entire history of discharge, the concentration and flux were normalized to remove year-to-year variability from input sources or management practices (Hirsch et al. 2010). A potential limitation of the WRTDS flow-normalization approach is the assumption of no changes in the long-term mean discharge, which clearly occur.

I utilized the Chesapeake Bay River Input Monitoring Network 1985-2022 Monthly loads Excel dataset, which provides TN and TP monthly export transported by the nontidal portion of the Choptank River in the Bay watershed (Mason et al. 2023). For this research, annual concentration and yield calculations considered the average monthly discharge reported in the monthly loads Excel dataset and the reported drainage area (293 km^2). The TN and TP concentration and yield were aggregated by progress year (July 1 to June 30) from 1985 to 2021.

4.2.4 Chesapeake Assessment Scenario Tool (CAST)

The online web interface of the Chesapeake Bay model, CAST, is a tool used to estimate nutrient export based on BMP implementation. Further details are provided in Chapter 3 methods. CAST also serves as a central repository of aggregated agriculture and baseline data. The data are submitted by federal and non-federal stakeholders and reviewed by EPA to ensure quality. For this research, I report the CAST-modeled nutrient export after BMP implementation in the Greensboro watershed land-river segment. I also report aggregated agricultural baseline data that may have influenced USGS observed nutrients and CAST-modeled nutrient export.

The CAST-modeled EOT nutrient loads were generated by the CAST web interface (version Phase 6-7.7.0) in June 2023 (described in Chapter 3 methods). This report provides nutrient export data on the mass per unit area from agricultural land uses. The EOT nutrient export models the TN and TP export that reaches the edge of the tidal portion of the Bay. In the case of the Greensboro watershed, the EOT is located at the USGS gauging station, and yield calculations were based on the land-river segment area (304 km^2). Estimated nutrient concentrations were based on EOT nutrient export data.

I compiled the following datasets from CAST for the Greensboro watershed land-river segment (described in Chapter 3 methods): nutrients inputs, manure nutrients available and applied, crop N and P needs, agricultural land BMPs, and animal waste management BMPs (Table 4.1). The land-based agricultural BMPs include BMPs reported by area measurements and animal waste management BMPs applied to livestock and poultry manure, implemented in the Greensboro watershed land-river segments. The agricultural BMP dataset excludes septic tank BMPs (measured by the number of tanks), stream bank BMPs (measured by linear length), and animal BMPs, such as manure storage, which are measured in animal units (AU). Other factors influencing TN and TP export are aggregating data associated with portions of Kent County, Delaware, outside the Chesapeake Bay watershed. County-level data include crop N and P needs, stored poultry manure N and P, livestock and poultry manure N and P, fertilizer, biosolids, and direct deposition onto pasture. Manure N and P input (kg ha^{-1} y^{-1}) calculations are based on reported county-level agricultural land use areas.

4.2.5 Statistical tests

Data were aggregated to the annual time scale of the progress year (July 1 to June 30) to remove seasonal variability. I used SigmaPlot v 15 to create linear regression plots. To test the significance of two linear regression models and slopes, I conducted a one-way ANCOVA (Analysis of Covariance) using the Holm-Sidak method for pairwise comparisons of factors. The results of statistical tests were categorized as significant (S, $p < 0.05$), marginally significant (MS, $0.05 \leq p < 0.10$), or not significant (NS, $p \geq 0.10$). The findings can be further verified by testing the trends using statistical tests accounting for autocorrelation in the time series.

4.3 Results: Measured and modeled water quality and N and P inputs

Measured and modeled nutrient export trends offer insight into the influence of agricultural land-based BMPs over the long-term water quality in the Greensboro watershed (Table 4.2). In this section, I present annual regional precipitation and watershed-scale discharge totals. I also assessed the influence of progress years, discharge, agricultural land-based BMPs, and animal waste management BMPs on nutrient export derived by three methods: (1) USGS field measurements, (2) the USGS WRTDS flow-normalization approach, and (3) CAST-modeling.

Table 4.2. Summary of nutrient concentration and yield trends. Abbreviations: “Fig.” represents the figure and panel, “Response” represents the parameter type, “x” represents the range of values for each response, and “p” represents the p-value. Bold text indicates no significant difference between the y-intercept or slope. Reference Tables 3 -7 for ANCOVA results.

Fig.	Response	y-intercept	slope	x	p
Annual Discharge (m^3 y^{-1}) and Precipitation (mm y^{-1}) Totals					
4.1	Annual discharge total 1975 – 2021	-2.30e+9	1.22e+6	1975-2021	0.04
4.1	Annual discharge total 1985 - 2021	-4.35e+9	2.24e+6	1985-2021	0.01
Average Nutrient Concentrations (mg L^{-1}) influenced by Progress Year					
4.2a	USGS TN measurements	-16.8	0.00930	1975-2021	0.0001
4.2b	WRTDS flow-normalization TN	-14.8	0.00830	1985-2021	0.0001
4.2c	CAST EOT TN	85.4	-0.0417	1985-2021	0.006
4.2d	USGS TP measurements	-2.86	0.00150	1970-2021	0.0001
4.2e	WRTDS flow-normalization TP	-2.63	0.00140	1985-2021	0.0001
4.2f	CAST EOT TP	8.37	-0.00410	1985-2021	0.0001
Annual Nutrient yields (kg ha^{-1} y^{-1}) influenced by Progress Year					
4.3a	USGS TN measurements	-301	0.155	1975-2021	0.0001
4.3b	WRTDS flow-normalization TN yield	-48.7	0.0284	1985-2021	0.0001
4.3c	CAST EOT TN yield	53.7	-0.0233	1985-2021	0.0001
4.3d	USGS TP measurements	-33.5	0.0170	1970-2021	0.0001
4.3e	WRTDS flow-normalization TP yield	-20.9	0.0107	1985-2021	0.0001
4.3f	CAST EOT TP yield	13.5	-6.60e-3	1985-2021	0.0001
Average Nutrient Concentrations (mg L^{-1}) influenced by Discharge (m^3 y^{-1})					
4.4a	USGS TN measurements	1.53	1.53e-9	0 – 3.00e+8	0.007
4.4b	WRTDS flow-normalization TN	1.72	4.19e-10	0 – 3.00e+8	0.163
4.4c	CAST EOT TN	6.97	exp(-1.07e-8)	0 – 3.00e+8	0.0001
4.4d	USGS TP measurements	0.0438	3.28e-10	0 – 3.00e+8	0.0001
4.4e	WRTDS flow-normalization TP	0.0687	9.47e-11	0 – 3.00e+8	0.03
4.4f	CAST EOT TP	0.503	exp(-1.33e-8)	0 – 3.00e+8	0.0001
Average Nutrient Concentrations (mg L^{-1}) influenced by Agricultural BMPs (km^2)					
4.5a	USGS TN measurements	1.67	6.00e-4	0 – 500	0.0001
4.5b	WRTDS flow-normalization TN	1.68	5.00e-4	0 – 500	0.0001
4.5c	CAST EOT TN	2.35	-2.50e-3	0 – 500	0.01
4.5d	USGS TP measurements	0.0643	1.78e-4	0 – 500	0.0001
4.5e	WRTDS flow-normalization TP	0.0664	9.01e-5	0 – 500	0.0001
4.5f	CAST EOT TP	0.146	-2.00e-4	0 – 500	0.0007
Annual Nutrient yields (kg ha^{-1}) influenced by Agricultural BMPs (km^2)					
4.6a	USGS TN measurements	6.37	0.0111	0 – 500	0.002
4.6b	WRTDS flow-normalization TN yield	7.91	2.02e-3	0 – 500	0.0001
4.6c	CAST EOT TN yield	7.34	-2.00e-3	0 – 500	0.0001
4.6d	USGS TP measurements	0.264	1.56e-3	0 – 500	0.0001
4.6e	WRTDS flow-normalization TP yield	0.448	7.24e-4	0 – 500	0.0001
4.6f	CAST EOT TP yield	0.452	-3.00e-4	0 – 500	0.0001
Average Nutrient Concentrations (mg L^{-1}) influenced by Animal Waste Management BMPs (AU)					
4.7a	USGS TN measurements	1.62	3.30e-6	0 – 110,000	0.0001
4.7b	WRTDS flow-normalization TN	1.64	2.78e-6	0 – 110,000	0.0001
4.7c	CAST EOT TN	2.59	-1.40e-5	0 – 110,000	0.0093
4.7d	USGS TP measurements	0.0467	1.01e-6	0 – 110,000	0.0001
4.7e	WRTDS flow-normalization TP	0.0586	4.86e-7	0 – 110,000	0.0001
4.7f	CAST EOT TP	0.173	-1.37e-6	0 – 110,000	0.0001
Annual Nutrient yields (kg ha^{-1}) influenced by Animal Waste Management (AU)					
4.8a	USGS TN measurements	5.34	6.15e-5	0 – 110,000	0.002
4.8b	WRTDS flow-normalization TN yield	7.79	9.60e-6	0 – 110,000	0.0001
4.8c	CAST EOT TN yield	7.38	-7.50e-6	0 – 110,000	0.0003
4.8d	USGS TP measurements	0.118	8.64e-6	0 – 110,000	0.0001
4.8e	WRTDS flow-normalization TP yield	0.386	3.90e-6	0 – 110,000	0.0001
4.8f	CAST EOT TP yield	0.468	-2.14e-6	0 – 110,000	0.0001

4.3.1 Time trends of annual precipitation totals and discharge

Figure 4.1 shows linear regression models depicting time trends of annual regional precipitation totals and watershed-scale discharge from 1970 to 2021. The Dover, Delaware regional average annual precipitation total between 1985 and 2021 is 1166 mm y^{-1} with large variability ranging from 756 mm in 2021 to 1654 mm in 2019 (NCEI-NOAA 2023) and is not significant ($p \geq 0.10$). Increasing annual discharge totals at the USGS gauging station are highly significant after 1985 ($p = 0.01$), with large interannual variability ranging from 46,203,555 m^3 in 1985 to 273,645,663 m^3 in 2021. An ANCOVA equal slopes test reveals no significant difference between the slopes and y-intercepts between 1975 and 2021 or 1985 and 2021 (Table 4.3).

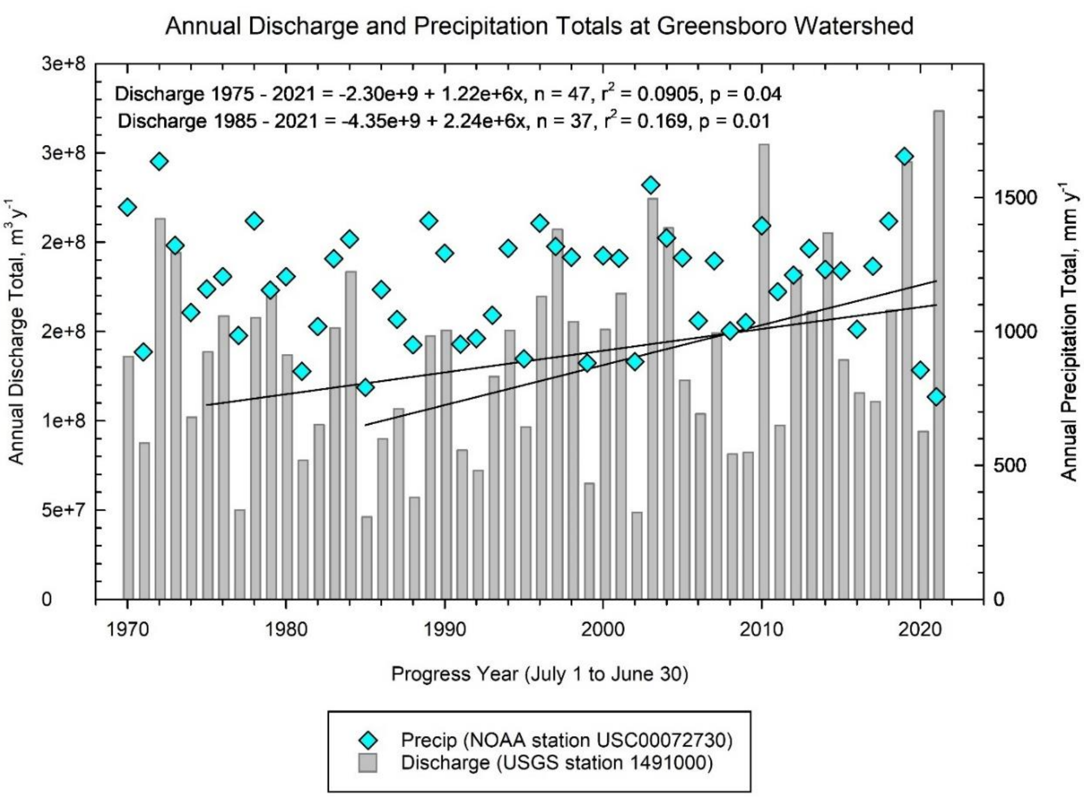


Figure 4.1. The annual watershed-scale discharge increased significantly between 1975 and 2021 and from 1985 to 2021 ($p \leq 0.05$). There were no detectable significant increases in the annual regional precipitation totals between 1970 and 2021 ($p > 0.1$).

Table 4.3. ANCOVA equal slopes test and equal slopes model (Fig. 4.1). Abbreviations: "Fig." represents figure and panel, "Group comparison" includes comparisons between USGS field measurements and the WRTDS flow-normalization approach applied by USGS, "Interp" provides an interpretation of ANCOVA results, "Adj. $\bar{x}$" represents the adjusted mean, "se" represents the standard error, and "p" represents the p-value.

		Equal Slopes Model					
Fig.	**Group comparison**	**slope**	**p**	**y-intercept**	**Adj. $\bar{x}$**	**se**	**p**
Annual Discharge (m^3 y^{-1}) and Precipitation (mm y^{-1}) Totals							
4.1	Annual discharge total 1975 – 2021	1.56e+6	NS	-2.97e+9	13.3e+7	9.0e+6	NS
4.1	Annual discharge total 1985 – 2021	1.56e+6		-2.97e+9	14.0e+7	7.9e+6	
	Interp: There is no significant difference between slopes and y-intercepts.						

4.3.2 Time trends of nutrient concentrations and yields

Despite CAST-modeled nutrient reductions, field measurements and WRTDS flow-normalized measurements of N and P concentrations significantly increased in the Greensboro watershed with progress years ($p < 0.0001$). The TN concentrations obtained through measurements (Fig. 4.2a) and the WRTDS flow-normalized approach (Fig. 4.2b) are not significantly different (Table 4.4) based on ANCOVA tests of the slopes and intercepts (Table 4.4). The USGS methods indicate that measured and flow-normalized TN concentrations increased in the Greensboro watershed from 1970 to 2021.

An ANCOVA equal slopes test of the P concentration based on field measurements (Fig. 4.2d) and WRTDS flow-normalized values (Fig. 4.2e) as a function of progress years also detected no significant differences in slope (Table 4.4). However, a subsequent analysis of the equal slopes models revealed that there is a significant difference in y-intercepts ($t = 3.94$, $p < 0.001$) where the field measurements (adj. $\bar{x} = 0.0935 \pm 0.00290$, CI[0.0877, 0.0993]) are greater than the WRTDS flow-normalization P concentration (adj. $\bar{x} = 0.0754 \pm 0.00346$, CI[0.0685, 0.0823]). The effect of WRTDS flow-normalization on P export was a 20 % reduction. In contrast, the CAST-modeled TN and TP concentrations (Figs. 4.2c, 4.2f) suggest initially higher and more variable concentrations in the 1980s than were observed. The CAST-modeled TN and

TP data decrease below the currently observed field measurements and WRTDS flow-normalized values by 2021.

The TN yields obtained through field measurements (Fig. 4.3a) increase faster than WRTDS flow-normalized TN yields (Fig. 4.3b) based on ANCOVA tests (Table 4.4, $p = 0.006$). The CAST-modeled TN yields (Fig. 4.3c) are higher than the measured values and approximately the same as the flow-normalized yields but slowly decreased from the 1980s to 2021, contrary to TN export values obtained through USGS methods. The measured TP yields (Fig. 4.3d) are lower and unrealistically near-zero around 1970, and the distribution of the yields suggests non-linear increases after ~1990. However, fewer monthly samples were measured between 1969 and 1974, which may bias the yield estimates, and consistent monthly sampling did not occur until 1975. Still, ANCOVA results indicate no significant differences between slopes and y-intercepts in Figures 3d and 3e (Table 4.4). The CAST-modeled TP yields (Fig. 4.3f) are higher than measured and flow-normalized values and decrease from 1985 to 2021. These data indicate that the CAST-modeled nutrient reductions (concentrations and yields) are not consistent with the USGS field observations or WRTDS flow-normalized TN and TP concentrations (Fig. 4.2) or yields (Fig. 4.3).

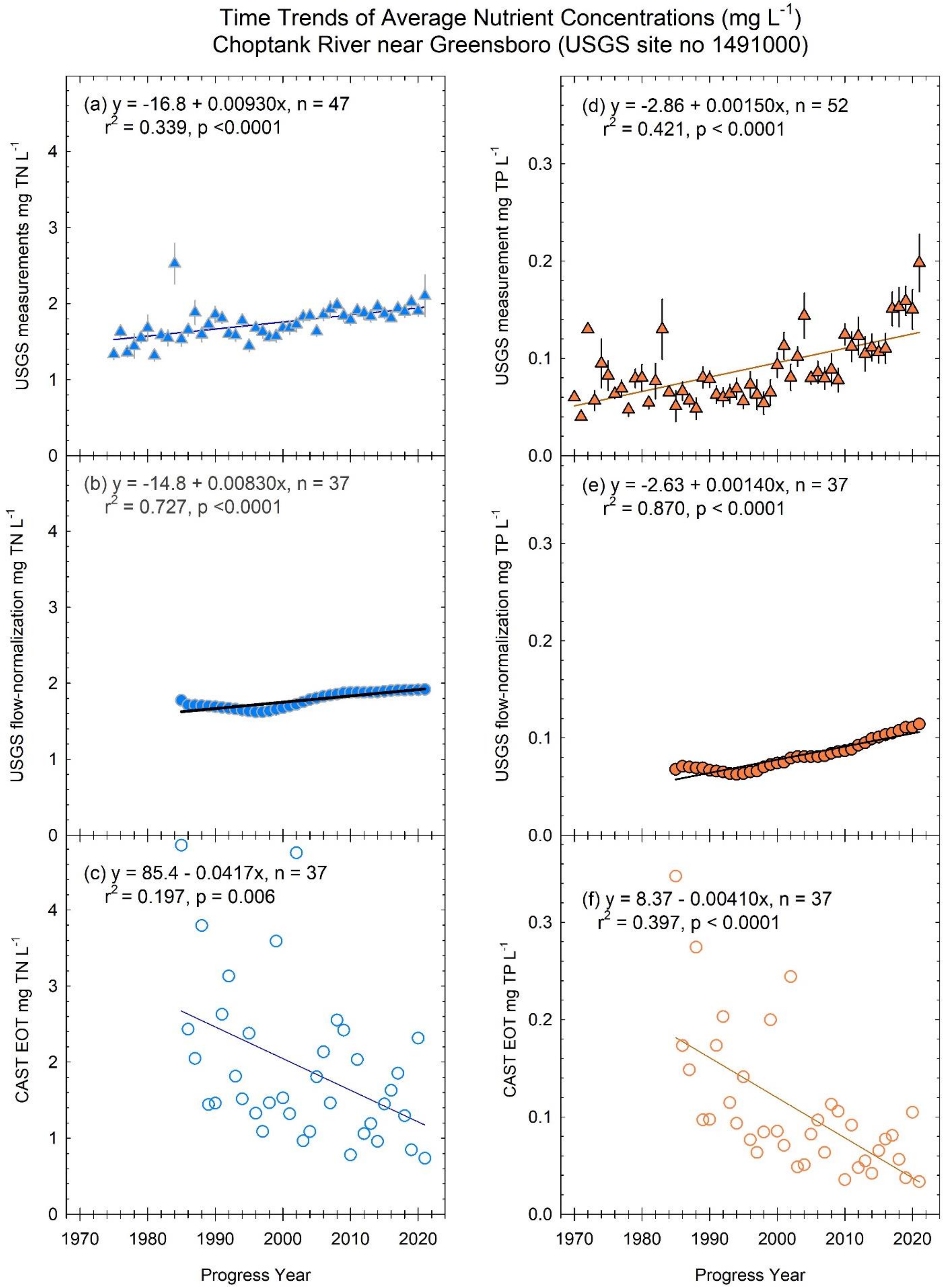


Figure 4.2. Measured, WRTDS flow-adjusted, and CAST-modeled TN and TP concentrations are shown as a function of progress year (July 1 to June 30).

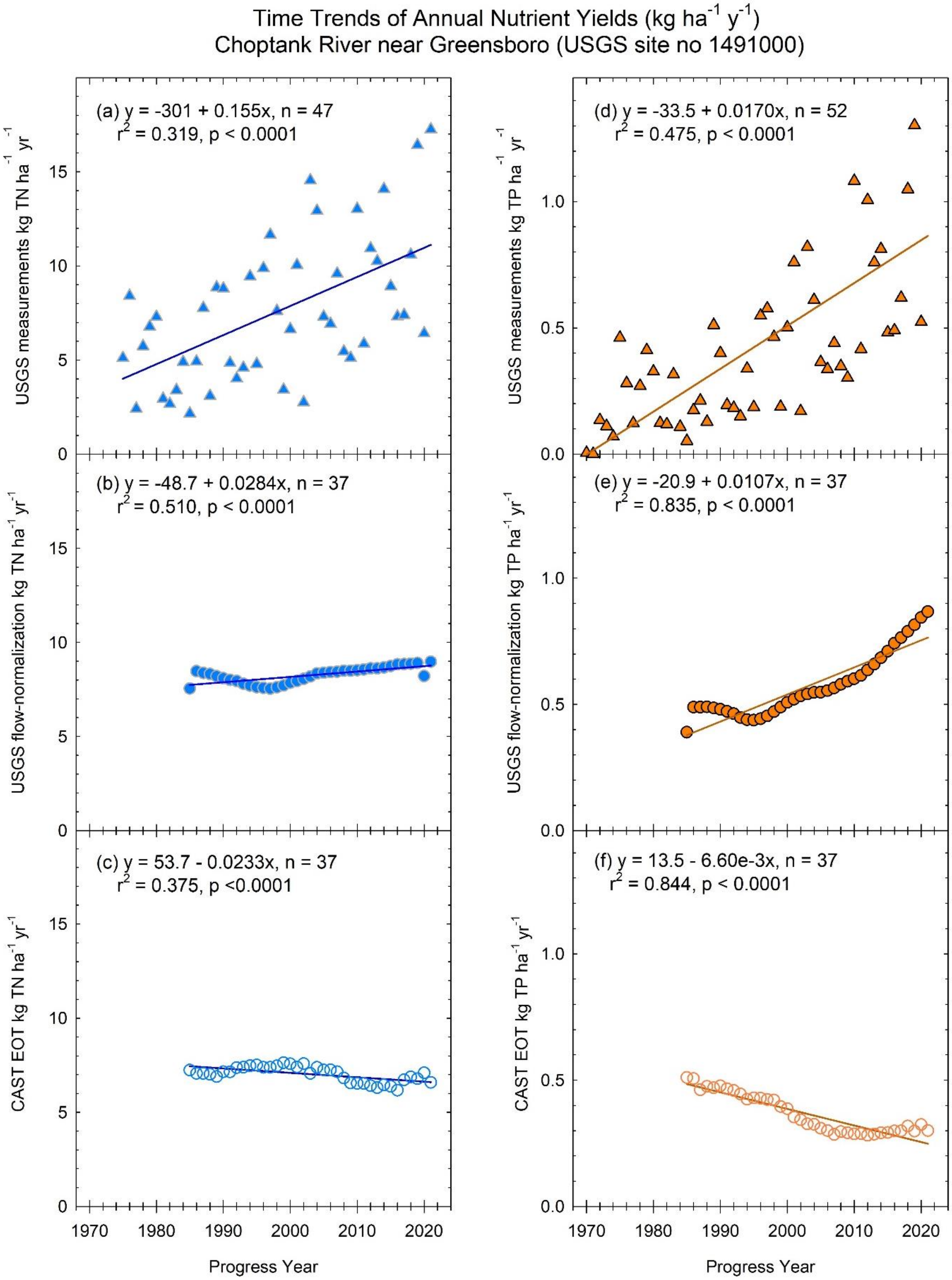


Figure 4.3. Measured, WRTDS flow-normalized, and CAST-modeled TN and TP yields are shown as a function of progress year. Panel d shows near zero TP yields between 1970 and 1980, partially due to fewer surface water samples from October 1969 to 1974. The data shown in Figure 4.3 are the same as in Figure 4.2, except the nutrient exports are expressed as yields (concentration x discharge/area).

Table 4.4. ANCOVA equal slopes test and equal slopes model (Figs. 4.2 and 4.3). Abbreviations: “Fig.” represents figure and panel, “Group comparison” includes comparisons between USGS field measurements and the WRTDS flow-normalization approach applied by USGS, “Interp” provides an interpretation of ANCOVA results, “Adj. $\bar{x}$” represents the adjusted mean, “se” represents the standard error, and “p” represents the p-value.

				Equal Slopes Model			
Fig.	**Group comparison**	**slope**	**p**	**y-intercept**	**Adj. $\bar{x}$**	**se**	**p**
Average Nutrient Concentrations (mg L^{-1}) influenced by progress year							
4.2a	USGS TN measurements	8.97e-3	NS	-16.2	1.76	0.0205	NS
4.2b	WRTDS flow-normalization TN export	8.97e-3		-16.2	1.75	0.0232	
	Interp: There is no significant difference between slopes and y-intercepts.						
4.2d	USGS TP measurements	1.45e-3	NS	-2.80	0.0935	0.00290	0.001
4.2e	WRTDS flow-normalization TP export	1.45e-3		-2.81	0.0754	0.00346	
	Interp: There is no significant difference between slopes, but the USGS TP measurements y-intercept is significantly greater than WRTDS flow-normalization TP export.						
Annual Nutrient Yields (kg ha^{-1} y^{-1}) influenced by progress year							
4.3a	USGS TN measurements	0.154	0.006	- -	- -	- -	- -
4.3b	WRTDS flow-normalization TN yield	0.0284					
	Interp: The slope in panel 3b is significantly greater than in panel 3a.						
4.3d	USGS TP measurements	0.0153	NS	-30.16	0.479	0.0302	NS
4.3e	WRTDS flow-normalization TP yield	0.0153		-30.14	0.504	0.0360	
	Interp: There is no significant difference between slopes and y-intercepts.						

4.3.3 Discharge trends of nutrient concentrations

Figure 4.4 shows discharge trends of nutrient concentrations based on three methods. Except for WRTDS flow-normalized TN concentrations (Fig. 4.4b), the concentrations of measured TN and TP and WRTDS flow-normalized TP increase slowly with increasing discharge (Figs. 4.4, panels a, d, and e). Discharge and concentrations increase with time, but concentrations (see Fig. 4.2) increase faster than discharge (Fig. 4.1). ANCOVA slope comparison tests reveal TP measurements (Fig. 4.4d) increase faster than USGS flow-normalization TP concentrations (Fig. 4.4e, Table 4.5, p = 0.015). In contrast, the CAST-modeled TN and TP concentrations decrease exponentially with discharge, clearly disagreeing with the USGS measurements and WRTDS values concerning discharge (Figs. 4.4c, 4.4f). The CAST model assumptions are based on an exponentially decreasing relationship between discharge and concentration, countering the WRTDS approach (Hirsch et al. 2010) and USGS field measurements. These data indicate the CAST-modeled relationship between nutrient concentrations and discharge is not well-supported by field measurements or WRTDS flow-normalized methods. Overall, TN and TP measured and WRTDS flow-normalized concentrations and yields increased with progress years (Figs. 4.2 and 4.3, panels a, b, d, and e) and discharge (Figs. 4.4, panels a, b, d, and e). In contrast, all CAST-modeled TN and TP

Table 4.5. ANCOVA equal slopes test and equal slopes model (Fig. 4). Abbreviations: "Fig." represents figure and panel, "Group comparison" includes comparisons between USGS field measurements and the WRTDS flow-normalization approach applied by UGS, "Interp" provides an interpretation of ANCOVA results, "Adj. $\bar{x}$" represents the adjusted mean, "se" represents the standard error, and "p" represents the p-value.

				Equal Slopes Model			
Fig.	**Group comparison**	**slope**	**p**	**y-intercept**	**Adj. $\bar{x}$**	**se**	**p**
Average Nutrient Concentrations (mg L^{-1}) influenced by Discharge ($m^3 y^{-1}$)							
4.4d	USGS TP measurements	3.28e-10	0.015	- -	- -	- -	- -
4.4e	WRTDS flow-normalization TP export	9.47e-11					
	Interp: The slope in panel 4d is significantly greater than in panel 4e.						

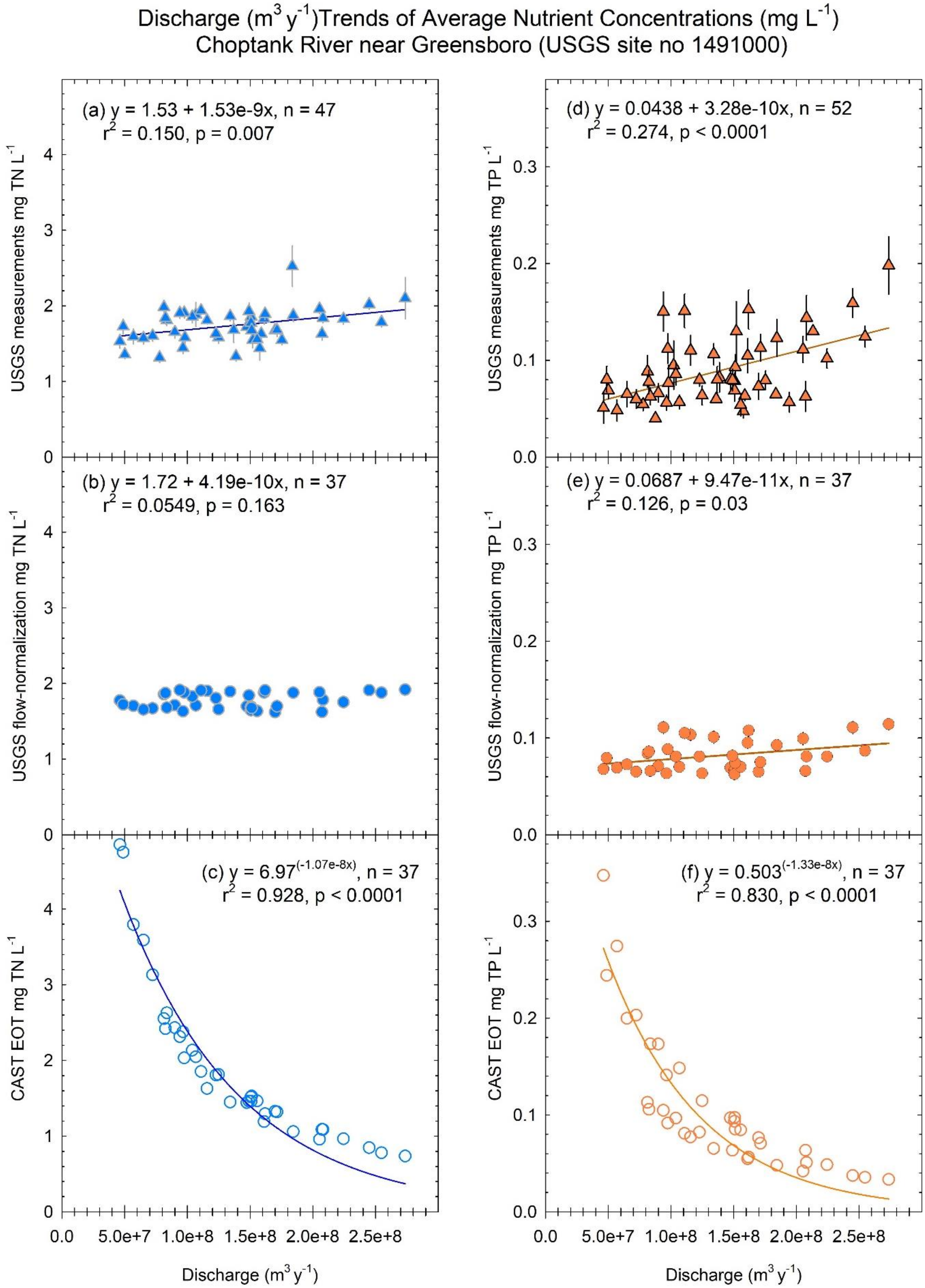


Figure 4.4. Measured, WRTDS flow-normalized, and CAST-modeled TN and TP concentrations are shown as a function of discharge.

concentrations and yields decrease with progress years and discharge (Figs. 4.1 and 4.3, panels c, f), clearly overestimating water quality improvements.

In the following sections, I present nutrient concentrations and yields influenced by watershed-scale agricultural land-based BMPs (Figs. 4.5 and 4.6) and animal waste management BMPs (Figs. 4.7 and 4.8). These BMPs were assessed in Chapter 3. Due to differences in units, agricultural land-based BMPs are presented separately from animal waste management BMPs in the figures shown in this chapter. Agricultural land-based BMPs are measured by area, and animal waste management BMPs are measured by animal units (AU). Both BMPs account for implementation in the Greensboro watershed land-river segment shown in Chapter 3 (Fig. 3.1).

4.3.4 Agricultural BMP trends of nutrient concentrations and yields

Measured, WRTDS flow-normalized, and CAST-modeled TN and TP concentrations (Fig. 4.5) and yields (Fig. 4.6) are shown as a function of cumulative agricultural land-based BMP areas in the Greensboro watershed. Between 1985 and 2021, the agricultural land area ranged from 112 – 123 km^2 (Source: CAST Loads Per Unit Report); however, in Figs. 4.5 and 4.6 agricultural BMP areas exceeded the agricultural land area available, indicating that multiple BMPs were applied in the watershed. There were no significant differences between the slopes and y-intercepts of TN concentrations derived from direct measurements (Fig. 4.5a) and WRTDS flow-normalized concentrations (Fig. 4.5b, Table 4.6), indicating either method describes the relationship between increasing TN export as agricultural land-based BMP areas increase ($p < 0.0001$). Additional ANCOVA tests reveal that direct USGS measurements result in faster

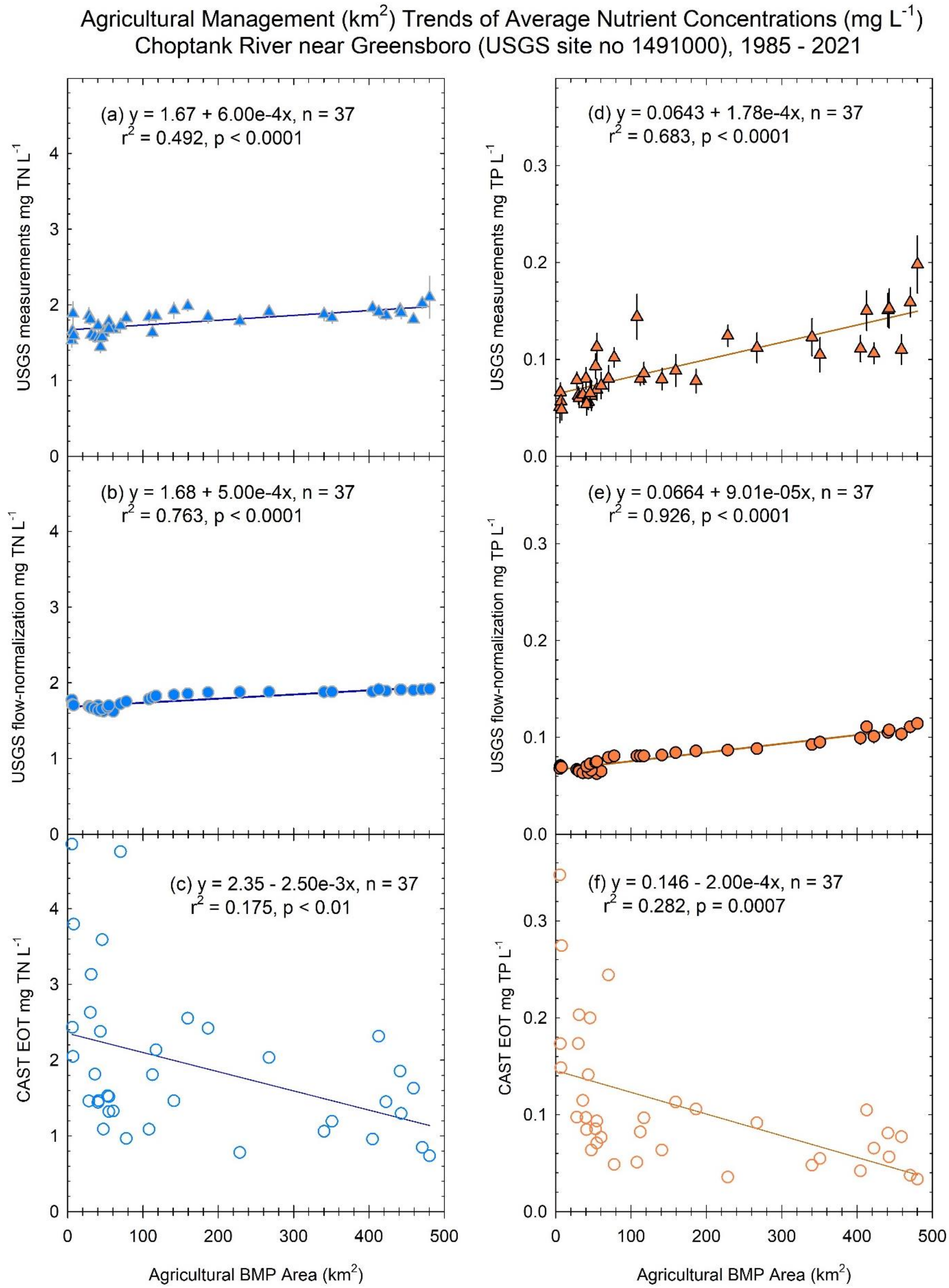


Figure 4.5. Measured, WRTDS flow-normalized, and CAST-modeled TN and TP concentrations are shown as a function of land-based agricultural BMPs.

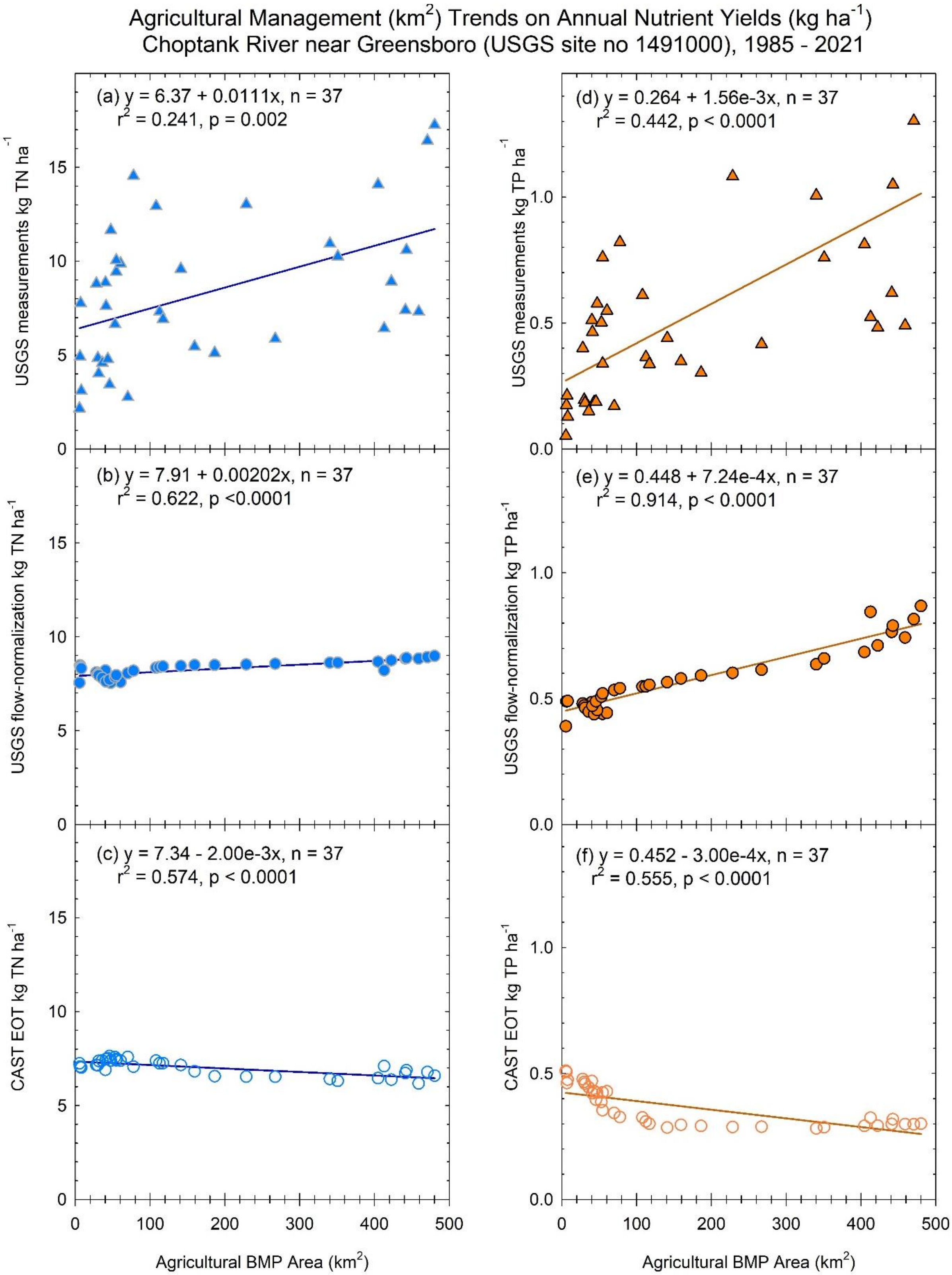


Figure 4.6. Measured, WRTDS flow-normalized, and CAST-modeled TN and TP yields are shown as a function of land-based agricultural BMPs. The data shown are the same in Fig. 5 but are expressed as TN and TP yields (kg ha^{-1}) from the Greensboro watershed (concentrations x discharge/area).

Table 4.6. ANCOVA equal slopes test and equal slopes model. Abbreviations (Figs. 4.5 and 4.6): “Fig.” represents figure and panel, “Group comparison” includes comparisons between USGS field measurements and the WRTDS flow-normalization approach applied by USGS, “Interp” provides an interpretation of ANCOVA results, “Adj. $\overline{x}$” represents the adjusted mean, “se” represents the standard error, and “p” represents the p-value.

				Equal Slopes Model			
Fig.	**Group comparison**	**slope**	**p**	**y-intercept**	**Adj. $\overline{x}$**	**se**	**p**
Average Nutrient Concentrations (mg L^{-1}) influenced by Agricultural BMPs (km^2)							
4.5a	USGS TN measurements	5.94e-4	NS	1.69	1.78	0.0142	NS
4.5b	WRTDS flow-normalization TN	5.94e-4		1.67	1.78	0.0142	
	Interp: There is no significant difference between slopes and y-intercepts.						
4.5d	USGS TP measurements	1.78e-4	0.001	- -	- -	- -	- -
4.5e	WRTDS flow-normalization TP	9.01e-5					
	Interp: The slope in panel 5d is significantly greater than panel 5e.						
Annual Nutrient Yields (kg ha^{-1}) influenced by Agricultural BMPs (km^2)							
4.6a	USGS TN measurements	0.0111	0.008	- -	- -	- -	- -
4.6b	WRTDS flow-normalization TN yield	0.00202					
	Interp: The slope in panel 6a is significantly greater than panel 6b.						
4.6d	USGS TP measurements	1.56e-3	0.007	- -	- -	- -	- -
4.6e	WRTDS flow-normalization TP yield	7.24e-4					
	Interp: The slope in panel 6d is significantly greater than panel 6e.						

increasing TP concentrations (Fig. 4.5d), TN yields (Fig. 4.6a), and TP yields (Fig. 4.6d) than the WRTDS flow-normalization approach applied by the USGS (Figs. 4.5, panels e, b, and e, Table 4.6).

Figure 4.5 shows that the CAST-modeled TN and TP concentrations in 1985 are much higher (1-4 mg N L^{-1} and 0.05-0.35 mg P L^{-1}) than measured and flow-adjusted concentrations shown in panels a and b and decrease to levels lower than USGS values as agricultural land-based BMPs increase (Figs. 4.5c, 4.5f). In contrast, the CAST-modeled TN yields (Fig. 4.6c) are similar to both the WRTDS flow-normalized TN yields and the measured data in 1985. However, by 2021, the CAST-modeled TN yields are much lower than TN yields based on USGS methods, decreasing as agricultural BMP areas increase. Figure 4.6f shows CAST-modeled TP yields start at yields similar to WRTDS flow-normalized yields (~0.5 kg P ha^{-1} y^{-1}). However, both of these estimated yields are nearly twice the measured yields shown in Figure 4.6d. By 2021, the CAST-modeled TP yields are much lower than both USGS yield datasets. This indicates poor modeling accuracy of measured and WRTDS flow-normalized concentrations by CAST. The USGS methods reveal differences in the rate of increase of TP concentration and TN and TP yields (Table 4.6); however, both methods show increasing yields as BMP areas increase.

4.3.5 Animal waste management trends of nutrient concentrations and yields

Measured, WRTDS flow-normalized, and CAST-modeled TN and TP concentrations (Fig. 4.7) and yields (Fig. 4.8) are shown as a function of animal waste management BMPs implemented in the watershed. No significant differences exist between the y-intercepts and slopes of TN concentrations derived from measured concentrations (Fig. 4.7a) and WRTDS flow-normalized concentrations (Fig. 4.7b, Table 4.7). Both sets of TN concentrations slightly increase as animal waste management BMPs increase, but the slope of measured TP concentrations (Fig. 4.7d) is significantly greater than WRTDS flow-normalized data (Fig. 4.7e, Table 4.7). Both USGS methods show significantly increasing TN and TP concentrations ($p < 0.0001$). In contrast, the CAST-modeled TN and TP concentrations (Figs. 4.7c, 4.7f) decrease significantly as animal waste management BMPs increase. Initially, the CAST-modeled TN and TP concentrations were much higher in 1985, and by 2021, CAST-modeled TN and TP concentrations were the lowest among the three methods. Figure 4.8 shows that both USGS methods significantly increase TN and TP yields ($p \leq 0.05$). However, the slopes of TN and TP yields based on field measurements (Figs. 4.8a, 4.8b) are significantly greater than the WRTDS flow-normalization approach (Figs. 4.8d, 4.8e, Table 4.7). The CAST-modeled TN yields in 1985 (Fig. 4.8c) are similar to the WRTDS flow-normalized TN yields and are slightly higher than measured TN yields. By 2021, the CAST-modeled TN yields will be much lower than both USGS TN yields, decreasing as animal waste management BMPs increase. Figure 8f shows CAST-modeled TP yields initially started in 1985 at yields similar to WRTDS flow-normalized yields, and both yields were originally much higher than the measured yields (Fig. 4.8d). By 2021, the CAST-modeled TP yields were much lower than both USGS yield datasets. These results indicate that USGS methods do not support CAST-modeled nutrient concentrations and yields.

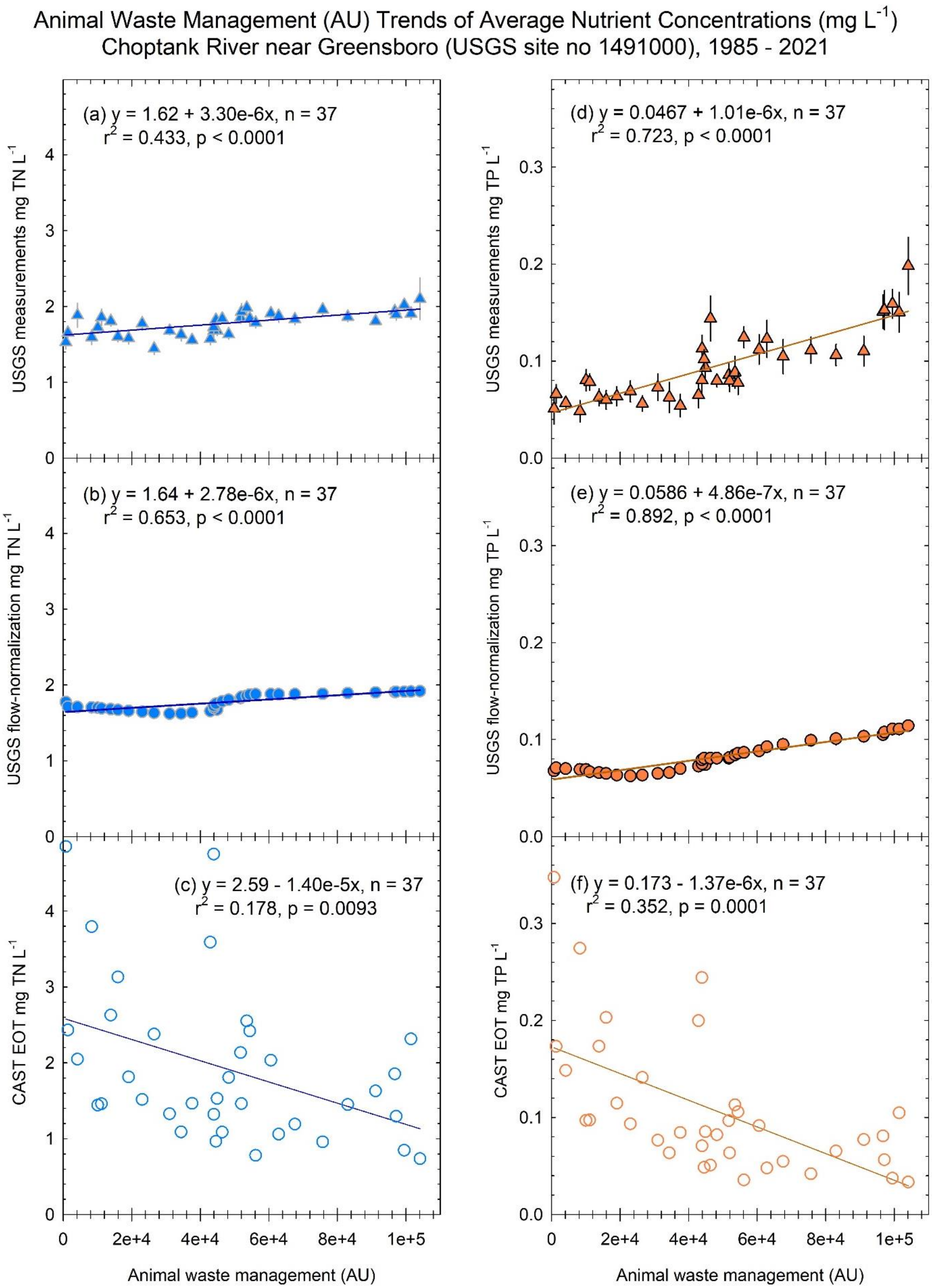


Figure 4.7. Measured, WRTDS flow-normalized, and CAST-modeled TN and TP concentrations are shown as a function of animal waste management BMPs (AU).

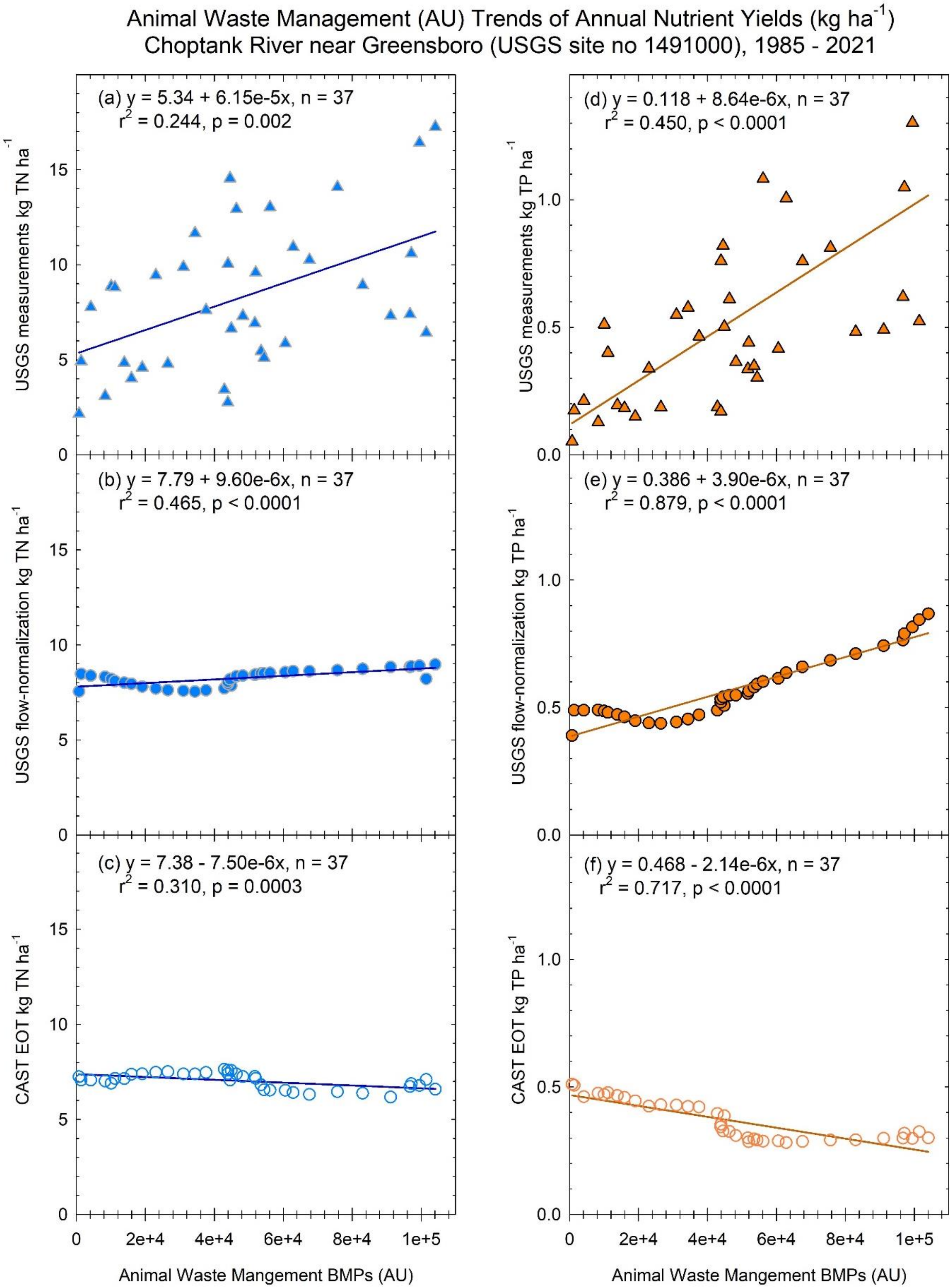


Figure 4.8. Measured, WRTDS flow-normalized, and CAST-modeled TN and TP yields are shown as a function of animal waste management BMPs (AU). The data shown are the same as depicted in Figure 4.7, except here, the values are expressed as TN and TP yields (kg ha^{-1}) from the Greensboro watershed (concentrations x discharge/area).

Table 4.7. ANCOVA equal slopes test and equal slopes model (Figs. 4.7 and 4.8). Abbreviations: "Fig." represents figure and panel, "Group comparison" includes comparisons between USGS field measurements and the WRTDS flow-normalization approach applied by USGS, "Interp" provides an interpretation of ANCOVA results, "Adj. $\overline{x}$" represents the adjusted mean, "se" represents the standard error, and "p" represents the p-value.

				Equal Slopes Model			
Fig.	**Group comparison**	**slope**	**p**	**y-intercept**	**Adj. $\overline{x}$**	**se**	**p**
Average Nutrient Concentrations (mg L^{-1}) influenced by Animal Waste Management BMPs (AU)							
4.7a	USGS TN measurements	1.63	NS	3.04e-6	1.78	0.0154	NS
4.7b	WRTDS flow-normalization TN yield	1.63		3.04e-6	1.78	0.0154	
	Interp: There is no significant difference between slopes and y-intercepts.						
4.7d	USGS TP measurements	1.01e-6	0.001	- -	- -	- -	- -
4.7e	WRTDS flow-normalization TP yield	4.86e-7					
	Interp: The slope in panel 7d is significantly greater than panel 7e.						
Annual Nutrient Yields (kg ha^{-1}) influenced by Animal Waste Management BMPs (AU)							
4.8a	USGS TN measurements	6.15e-5	0.006	- -	- -	- -	- -
4.8b	WRTDS flow-normalization TN yield	9.60e-6					
	Interp: The slope in panel 8a is significantly greater than panel 8e.						
4.8d	USGS TP measurements	8.64e-6	0.005	- -	- -	- -	- -
4.8e	WRTDS flow-normalization TP yield	3.90e-6					
	Interp: The slope in panel 8d is significantly greater than panel 8e.						

4.3.6 Time trends of nutrients applied in the tri-county region

Figure 4.9 shows the time trend of annual total N and P inputs from four sources applied to agricultural land uses in the tri-county region. The data shown in Figure 4.9 are only available at the county scale, and the Greensboro watershed lies at the intersection of three counties, Kent County, Delaware, and two Maryland counties, Queen Anne's and Caroline (Fig. 3.1), which explains why some figures in this discussion depict aggregated data tri-county region. Input sources include manure, fertilizer, and biosolids applied onto cropland and direct deposition of animal waste on pasture. The stored poultry manure includes locally produced manure and manure transported into the tri-county region. The crop N and P needs (red dash line) are modeled estimates based on the amount of N and P needed to support average crop yields under typical conditions (CBP 2019). Decreasing N and P crop needs after 2010 likely responded to declining corn production and increasing soybean plantings in one or more of the Greensboro watershed counties.

Tri-county level N inputs significantly increased between 1985 and 2021 ($p < 0.0001$) (Fig. 4.9a), which met or exceeded crop N needs during most progress years. Since 2011, N inputs have exceeded crop N needs and may have increased N concentrations at the USGS gauging station. In contrast, tri-county level P inputs decreased even as poultry and livestock manure applications increased since 2000 ($p < 0.0001$, Fig. 4.9b). The P inputs rarely met estimated crop P needs between 1985 and 2021. This apparent P input imbalance does not explain the increases in P export measured at the USGS gauging station.

Fertilizers, manure, biosolids, and direct deposition contribute unequal amounts of N and P annually (Fig. 4.10). The N and P inputs from biosolids onto cropland are less than 5% for P and 3% for N. Direct manure deposition onto pasture is also small and ranges from 3% to 6% for

N and P. Manure locally produced or imported into the tri-county region and commercial fertilizer contribute the most N and P onto croplands in the tri-county region. The N contributions from fertilizer and manure range from 57 – 73% and 20 –39% of the annual total N inputs (Fig. 4.10a). Fertilizer contributes the highest source of N annually; however, fertilizer N contributions have decreased as manure N increased ($p < 0.0001$). The fertilizer P and manure P contributions vary from 27 – 68% and 23 – 68% of the annual total P inputs (Fig. 4.10b). Figure 4.10b shows fertilizer P contributions have decreased as manure P inputs have increased. However, after 2008, livestock and poultry manure has been the dominant source of P. The livestock and poultry manure are likely stored using animal waste management BMPs (Fig. 2.6), revealing that nearly all the applied manure originates from poultry (black dash-dot line).

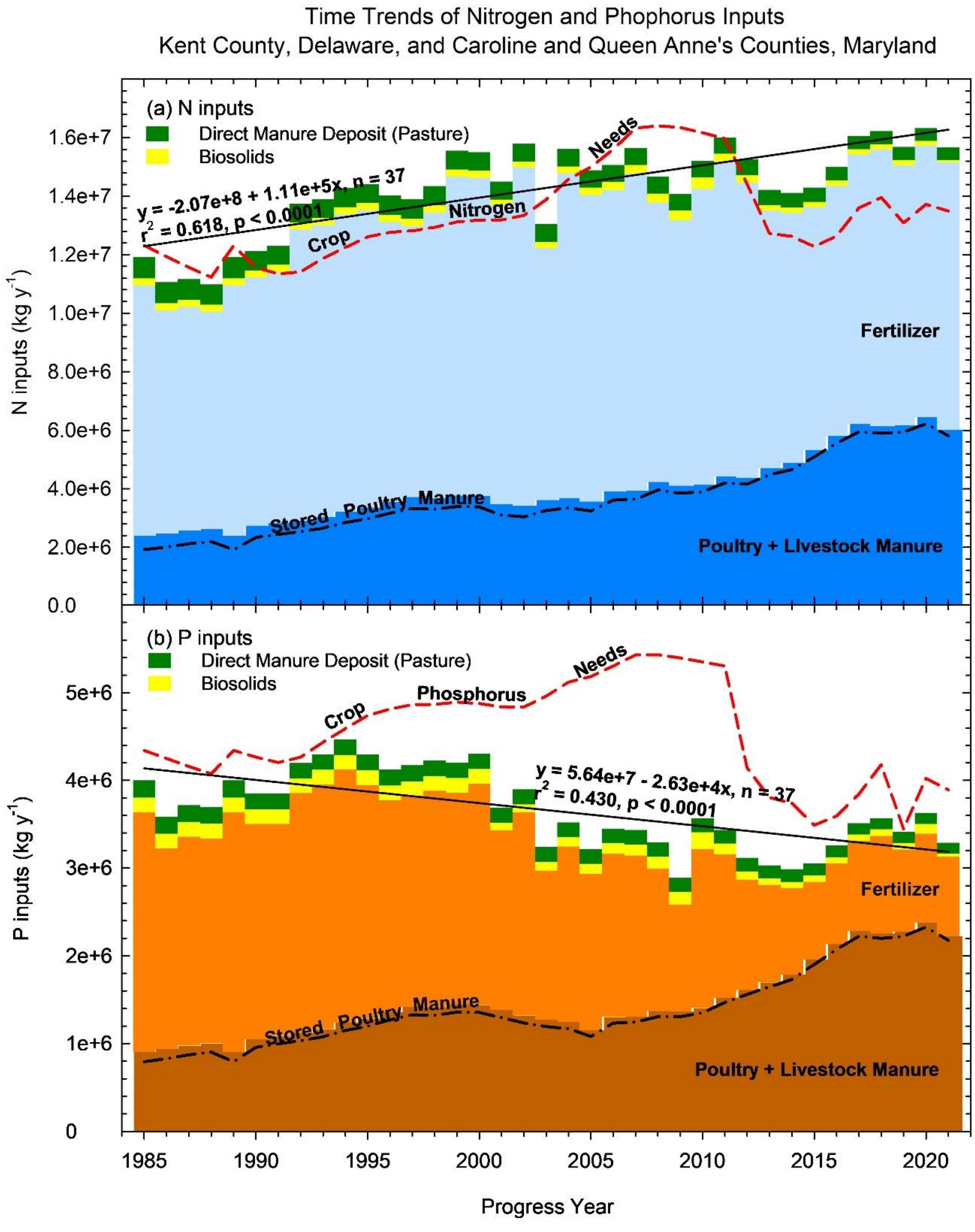


Figure 4.9. The N and P inputs and Crop N and P needs in the tri-county region (Kent County, Delaware and Maryland counties, Queen Anne's and Caroline) are shown as a function of progress year. Nutrients include commercial fertilizer, biosolids, direct manure deposition onto pasture, and livestock and poultry manure. The amount of N and P needed to support average crop yields is estimated under typical conditions. Applied poultry and livestock manure is equivalent to the amount stored in each county. Most of the applied manure originates from stored poultry manure in manure sheds. The stored manure includes locally produced manure and manure transported into the tri-county region. Data sources: CAST Nutrients Applied Report and CAST Manure Nutrients Available Report.

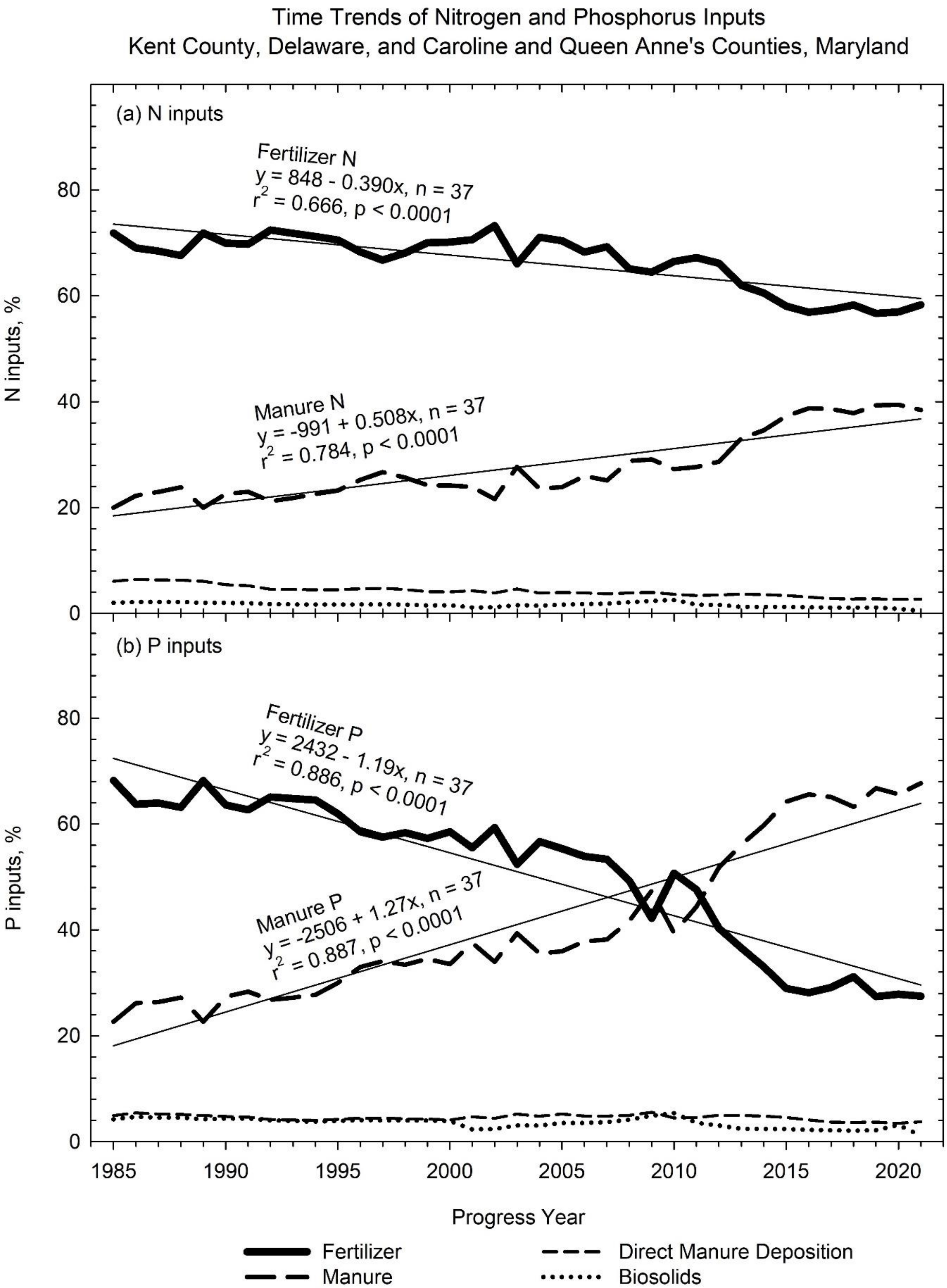


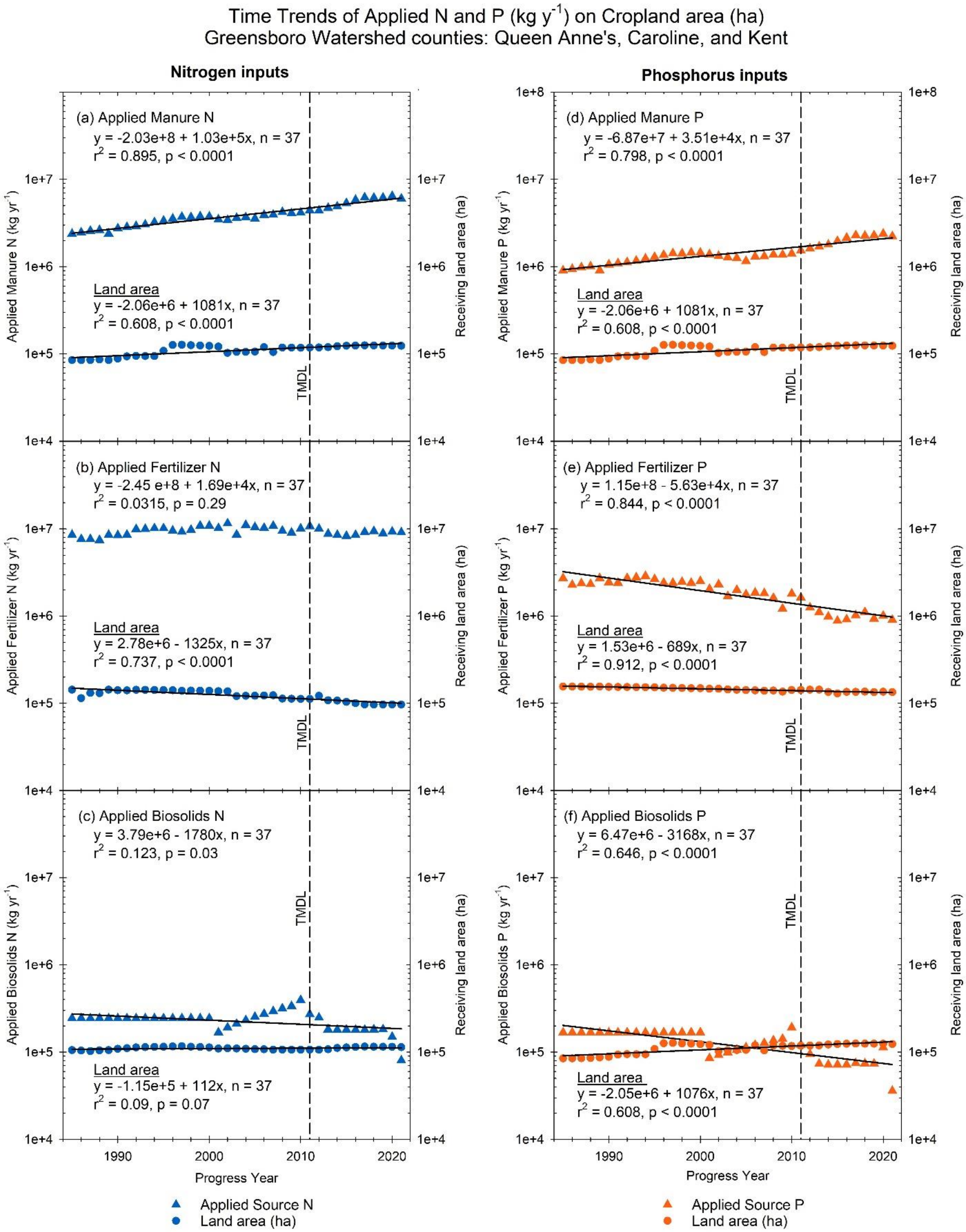
Figure 4.10. The percentage of fertilizer, manure, biosolids, and direct manure deposition contributions to N and P inputs are shown in panels a and b, respectively. Data source: CAST Nutrients Applied Report

4.3.7 Applied Manure, Fertilizer, Biosolids Applied onto Croplands

The area of croplands receiving N and P inputs from manure (Figs. 4.11ad) has not increased as rapidly as the annual application amounts (mass) and rates (per hectare). Figure 4.11 shows increasing applications of manure N and P ($p < 0.0001$) as the amount of agricultural land receiving manure applications increased by only 11 km^2 y^{-1} in the tri-county region between 1985 and 2021 (panels a and d). Consequently, manure N and P application rates have increased significantly from 1985 to 2021 ($p < 0.0001$, Figs. 4.12a, 4.12b).

The largest source of nonpoint P contribution to surface waters is a direct result of manure application (Figs. 4.9, 4.10). Manure collected from poultry houses on the Eastern Shore has traditionally been applied to fields near the operation to improve the soil and provide nutrients for crop production (Staver et al. 1995; Ator et al. 2015). Additionally, increasing poultry production in the Greensboro watershed and the high-priced cost of manure transport have left no cost-effective alternatives for farmers but to apply manure onto nearby croplands (Mukhtar 2005; Swaney et al. 2018). Consequences of manure overapplications result in manure nutrient application rates above crop demand and declining crop nitrogen use efficiency (NUE) (Klinglmair et al. 2015; Swaney et al. 2018). Additionally, the long-term manure application to soils at rates exceeding crop uptake can result in elevated soil-P levels (Staver et al. 1995; Ator et al. 2015), and Staver et al. (1995) found that manure applied to no-till soils increased soluble P in overland flow.

Figure 4.11. Log-scale values reflect the applied N and P from manure, fertilizer, and biosolids shown in Figure 4.9 and the amount of receiving cropland areas in Caroline and Queen Anne's Counties, MD, and Kent County, DE, between 1985 and 2021. These sources of N and P are applied to agricultural land uses in counties containing the Greensboro watershed, including portions of Kent County, Delaware, located inside and outside the Chesapeake Bay watershed between 1985 and 2021. Data sources: CAST Nutrients Applied Report.



Time Trends of Applied N and P (kg y-1) on Cropland area (ha)
Greensboro Watershed counties: Queen Anne's, Caroline, and Kent
Nitrogen inputs
Phosphorus inputs
(a) Applied Manure N
y = -2.03e+8 + 1.03e+5x, n = 37
r2 = 0.895, p < 0.0001
Land area
y = -2.06e+6 + 1081x, n = 37
r2 = 0.608, p < 0.0001
(b) Applied Fertilizer N
y = -2.45 e+8 + 1.69e+4x, n = 37
r2 = 0.0315, p = 0.29
Land area
y = 2.78e+6 - 1325x, n = 37
r2 = 0.737, p < 0.0001
(c) Applied Biosolids N
y = 3.79e+6 - 1780x, n = 37
r2 = 0.123, p = 0.03
Land area
y = -1.15e+5 + 112x, n = 37
r2 = 0.09, p = 0.07
(d) Applied Manure P
y = -6.87e+7 + 3.51e+4x, n = 37
r2 = 0.798, p < 0.0001
Land area
y = -2.06e+6 + 1081x, n = 37
r2 = 0.608, p < 0.0001
(e) Applied Fertilizer P
y = 1.15e+8 - 5.63e+4x, n = 37
r2 = 0.844, p < 0.0001
Land area
y = 1.53e+6 - 689x, n = 37
r2 = 0.912, p < 0.0001
(f) Applied Biosolids P
y = 6.47e+6 - 3168x, n = 37
r2 = 0.646, p < 0.0001
Land area
y = -2.05e+6 + 1076x, n = 37
r2 = 0.608, p < 0.0001
TMDL
Applied Manure N (kg yr-1)
Applied Fertilizer N (kg yr-1)
Applied Biosolids N (kg yr-1)
Applied Manure P (kg yr-1)
Applied Fertilizer P (kg yr-1)
Applied Biosolids P (kg yr-1)
Receiving land area (ha)
1e+4
1e+5
1e+6
1e+7
1e+8
1990
2000
2010
2020
Progress Year
Applied Source N
Land area (ha)
Applied Source P
Land area (ha)

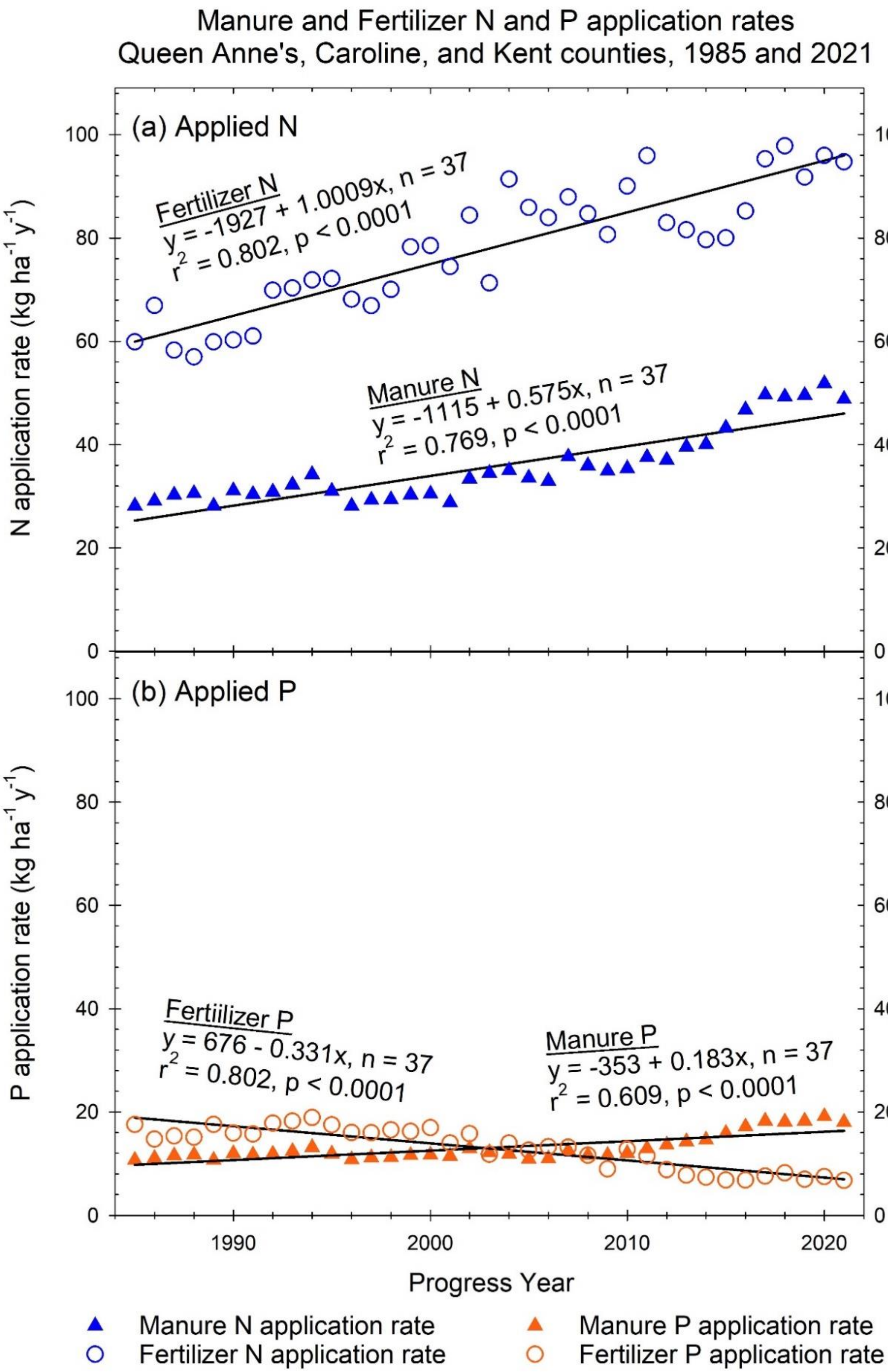


Figure 4.12. The fertilizer and manure N and P data shown are the same in Figure 4.11, but expressed as kg ha^{-1} y^{-1}.

Figure 4.11b shows fertilizer N inputs are much higher than manure N inputs but do not show significant increases in annual fertilizer N inputs ($p \geq 0.10$). However, the area of croplands receiving N fertilizer decreased between 1985 and 2021 (Fig. 4.11b, $p < 0.0001$). Consequently, the fertilizer N application rate increased by 1.0009 kg ha^{-1} y^{-1} (Fig. 4.12a). In contrast, as annual manure P applications increased ($p < 0.0001$, Fig. 4.11d), fertilizer P and the receiving land areas decreased ($p < 0.0001$, Figs. 4.11e). The data indicate that fertilizer P application rates decreased by 0.331 kg ha^{-1} y^{-1} as manure P application rates increased by 0.183 kg ha^{-1} y^{-1} and surpassed the application rate of fertilizer P by 2003 (Fig. 4.12b). The data support a shift in obtaining P from commercial fertilizer to more cost-effective manure sources (Sharpley et al. 1994).

Figure 4.10 shows a small percentage contribution of N and P from biosolids onto croplands. Biosolids N and P contributions decreased as the land area receiving these inputs increased (Figs. 4.11c, 4.11f), indicating a declining application rate. Overall, the data shown in Figures 4.11 and 4.12 indicate high amounts of fertilizer N and manure N and P were applied to a disproportionate amount of agricultural croplands. These data support cropland intensification due to increasing N and P applications to croplands due to commercial fertilizer and poultry manure (Fisher et al. 2006a; Fisher et al. 2010; USEPA 2010c; Kleinman et al. 2019).

4.3.8 N and P watershed inputs and outputs

A summary of watershed N and P balances is shown in Figure 4.13. Manure N and P inputs in all panels increased between 1970 and 2021 ($p < 0.0001$). As manure N and P inputs increased, the export of N and P at the USGS gauge increased only in the measured and WRTDS flow-normalize data (Figs. 4.13, panels a, b, d, and e). The measured and WRTDS flow-normalization N and P export were decreasing fractions of the manure inputs. The nutrient export at the watershed outlet represented, on average, < 25% of manure N inputs and < 5% of manure P inputs with large interannual variability. Much of the N inputs are used by crops to achieve grain yields and can result in reduced N export. An empirical study by Staver (2001) found that corn could reduce soil nitrate concentrations in the top 30 cm of the root zone to < 1 mg kg^{-1}in croplands that received N applied via fertilizer and poultry manure. Low P export can be partially explained by higher P accumulation rates in soils sampled in dense poultry production areas observed in Delmarva (Sharpley et al. 1994; Noe et al. 2005; Vaughan et al. 2007). ANCOVA equal slopes tests showed that manure N and P input slopes are significantly greater than the nutrient export slopes shown in each panel ($p < 0.001$), indicating manure inputs outpace TN and TP exports and potential N and P storage in the watershed. The export also increases over time, resulting from increasing soil P saturation and N mobility via groundwater.

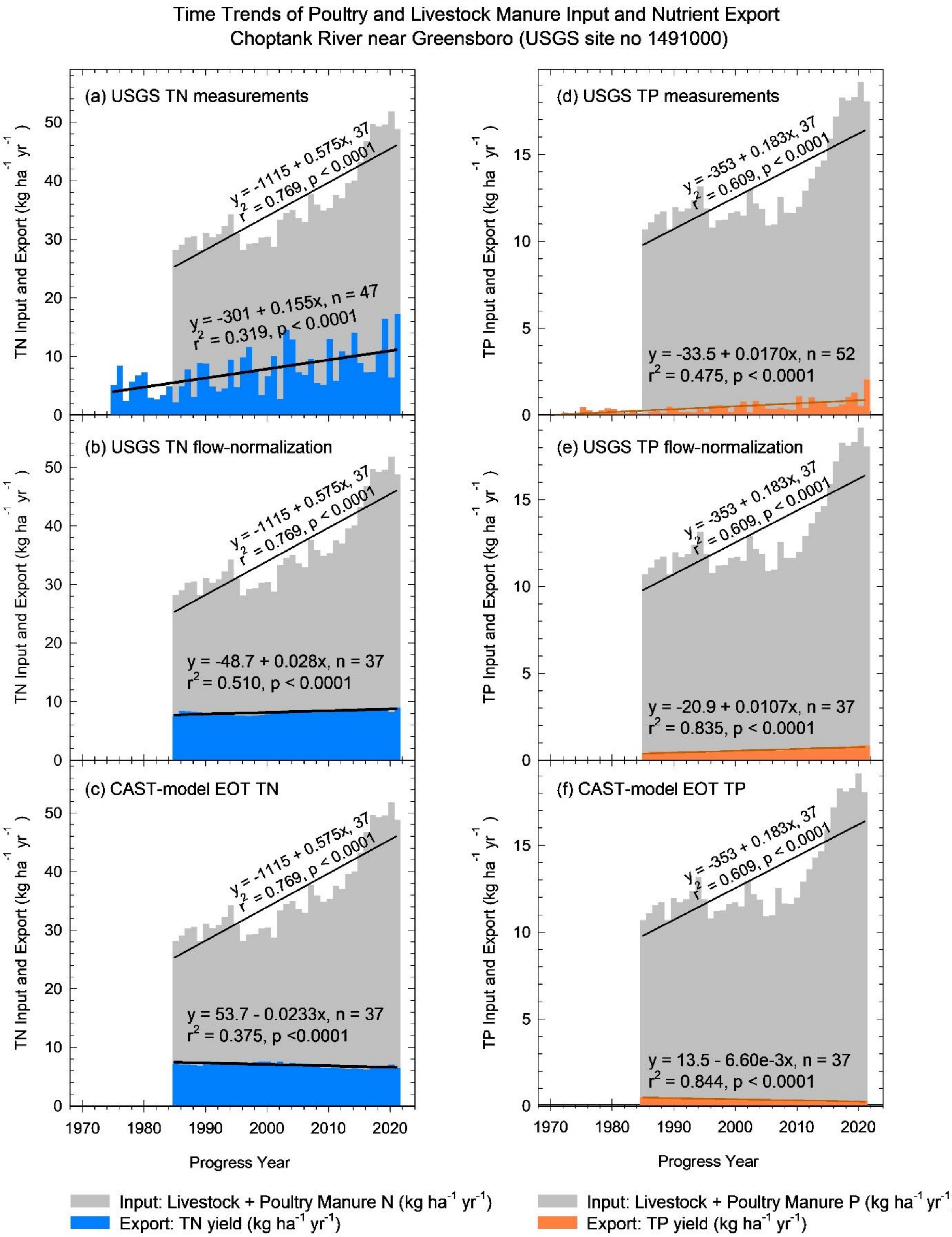


Figure 4.13. Measured, WRTDS flow-normalized, and CAST-modeled TN and TP yields (export) and aggregated county-level livestock and poultry manure inputs are shown as a function of progress years. The same manure N input data are shown in panels a, b, and c, and panels d, e, and f show the same manure P inputs. Figure 4.3 shows the same watershed-scale TN and TP yields (export). Figure 4.12a shows the same manure N inputs. Figure 4.12b shows the same manure P inputs.

4.5 Discussion

4.5.1 Test of the hypothesis

I assessed the influence of progress years, annual discharge, agricultural land-based BMPs, and animal waste management BMPs on nutrient concentrations and yields derived from three methods: USGS field measurements, the WRTDS flow-normalization approach used by the USGS, and CAST modeling. The results from CAST modeling support the hypothesis that the historical nutrient data at the Greensboro USGS gauge are related to BMP implementation. However, the USGS methods for estimating nutrient concentrations and yields do not agree with the CAST model outputs and do not support the hypothesis that the three methods are in agreement. Table 4.8 summarizes trends based on the influence of progress years, discharge, and BMPs on nutrient concentrations and yields estimated by USGS field measurements, USGS flow-normalization, and CAST modeling. Overall, the USGS data consistently indicate increasing nutrient concentrations and yields. Conversely, CAST modeling shows decreasing nutrient trends.

In the following discussion, I synthesize factors influencing nutrient export: overestimating BMP nutrient removal performance, intensive agriculture, model parameters, and climate change. These factors provide a basis for improved future modeling efforts and land management. I recommend using adjusted BMP efficiencies during cultural and structural BMP lifespans to improve model outputs. I also suggest two approaches to reflect the role of annual poultry manure applications: (1) model nutrient transport via artificial drainage ditches that interfere with natural nutrient flow pathways and exacerbate N and P transport (Sharpley et al. 2006; Kleinman et al. 2007; Needelman et al. 2007; Carstensen et al. 2020) and (2) model the

Table 4.8. Summary of nutrient concentrations and yields shown in Figures 2 - 8. Abbreviations: "Fig." represents the figure number followed by concentration (conc.) or yield, TN and TP data are based on "FM" = USGS field measurements, "FN" = WRTDS flow-normalized approach used by the USGS, "CAST" = Chesapeake Assessment Scenario Tool. For each reported result, "+" indicates an increasing trend, and "-" indicates a decreasing trend. Beneath each trend, the p-value is reported.

		TN			**TP**		
Covariate	**Fig. # and type**	**FM**	**FN**	**CAST**	**FM**	**FN**	**CAST**
Progress year	2. conc.	+ 0.0001	+ 0.0001	- 0.006	+ 0.0001	+ 0.0001	- 0.0001
	3. yield	+ 0.0001	+ 0.0001	- 0.0001	+ 0.0001	+ 0.0001	- 0.0001
Discharge	4. conc.	+ 0.007	0.163	- 0.0001	+ 0.0001	+ 0.03	- 0.0001
Agricultural land-based BMPs	5. conc.	+ 0.0001	+ 0.0001	- 0.0001	+ 0.0001	+ 0.0001	- 0.0007
	6. yield	+ 0.002	+ 0.0001	- 0.0001	+ 0.0001	+ 0.0001	- 0.0001
Animal waste management BMPs	7. conc.	+ 0.0001	+ 0.0001	- 0.0093	+ 0.0001	+ 0.0001	- 0.0001
	8. yield	+ 0.002	+ 0.0001	- 0.0003	+ 0.0001	+ 0.0001	- 0.0001

accumulation of soil-P and saturated soil-P, resulting in increases in dissolved P and particulate P in downstream surface waters (Sharpley et al. 2002). Agronomic recommendations include developing efficient manure recycling approaches within the local agricultural systems via nutrient management practices and concurrent research and development to support alternative uses of animal waste, including composting, bioenergy generation, granulating/pelletizing, and establishing a marketplace to support the sale of these products and to offset the costs of transporting manure from areas of manure surplus to manure deficit areas (Sharpley et al. 2010; Spiegal et al. 2020; Lim et al. 2023).

4.5.2 Overestimating nutrient removal performance

Intensive agriculture has contributed a disproportionate amount of N and P to fresh, estuarine, and coastal waters worldwide (Foley et al. 2005; Howden et al. 2013; Svanback et al. 2019; Zou et al. 2020). For example, fertilizer and manure applications in China contributed over 70% of TN and TP between 1978 and 2017 (Zou et al. 2020)and 54% of N and 43% of P in the Chesapeake Bay (Ator et al. 2011). Thus, the potential to reduce agricultural nonpoint sources can be significant by implementing the most effective BMPs for reducing N and P.

Management practices that effectively reduce N and P in the Chesapeake Bay watershed include animal waste management and soil tillage (Sekellick et al. 2019). Hence, animal waste management systems significantly increased, and farmers applied conservation tillage practices to nearly all croplands in the Greensboro watershed (Figs. 2.4 and 2.6). In turn, modeled N and P concentrations and yields reflected the expected decline in nutrient concentration and yields (Figs. 4.7 and 4.8). Conversely, measured N and P concentrations and yields have increased in parallel with the increasing use of animal waste management practices (Figs. 4.7 and 4.8) and other agricultural BMPs (Figs. 2.4 and 2.5). Fanelli et al. (2019) also found that manure applications and conservation tillage correlated with changes in P concentrations at high flow, suggesting that these activities could increase P concentrations and partially explain increasing P export at the USGS gauge. In the following sections, I explore applications of animal waste management and soil tillage practices, the consequences of intensive agriculture, discrepancies observed in modeling and measurable water quality responses, and uncertainty due to climate change.

Animal waste management

In areas of high livestock production, few animal waste management practices can efficiently recycle nutrients in the agroecosystems. Manure surplus exceeds the assimilative capacity of limited croplands to receive manure applications (Kellogg et al. 2014). Instead, animal waste management practices have become responsible for safely storing manure surpluses, not reducing nutrients, as Sekellick et al. (2019) and Pearce et al. (2017) suggest. Manure injection and incorporation management practices also aim to recycle manure within croplands. (Mostaghimi et al. 2001; Dell et al. 2016; Pickford 2022).

However, the safe storage of manure for planned applications on cropland combined with manure injection and incorporation practices do not reduce nutrients. Instead, animal waste management practices are BMPs that promote the safe storage of manure until environmental conditions are suitable for manure application onto cropland or pasture and can be applied locally or transported elsewhere (Mukhtar 2005; Hawkins et al. 2016). Similarly, manure incorporation and injection require incorporating manure directly into the soil profile in 1 to 3 days and injections within 24 hours, aiming to lower ammonia-N volatilization and dissolved P and N losses via overland flow. (Dell et al. 2016).

Additionally, extended periods permitting manure spreading lessen the burden of storing manure surpluses, given limits to manure storage shed capacity (Staver 2001). The 2022 winter ban on spreading manure in Maryland took effect on December 16 and ended on March 1 (per Maryland Department of Agriculture). Delaware's Nutrient Management Law prohibits manure spreading from December 7 to February 15. However, model results reported by Liu et al. (2017a) show increased annual TP and dissolved P losses during fall and winter compared to spring applications in an upland agricultural watershed in south-central Pennsylvania. Moreover, in areas of intensive livestock production, there are higher risks of nutrients in manure used for crop production more than crop requirements and applied to croplands that can no longer assimilate the added manure N and P, which can result in N and P leaching and overland flow (Petersen et al. 2007; Kellogg et al. 2014). Therefore, program managers and policy-makers should establish incentives to move manure from surplus regions to deficit regions to increase manure recycling (Spiegal et al. 2020). At a local level, pursue additional research and development to efficiently use manure in crop production via nutrient management practices, which can decrease imports of mineral fertilizers (Svanback et al. 2019).

Soil tillage practices

Conventional and conservation tillage practices prepare the seedbed for planting, weed control, and soil moisture preservation (Wade et al. 2015). Different types of soil tillage can result in varying degrees of soil erosion and overland flow due to the percent of ground cover remaining on the cropland immediately after tilling (Table 4.9). Generally, conventional or high tillage practices can increase soil erosion and overland flow. Conservation tillage practices and high residue tillage leave at least 30% of ground cover, can greatly decrease soil erosion and overland flow, and improve the physical, chemical, and biological soil properties (Smith 2007; Wade et al. 2015; Bauer et al. 2020; Luetzenburg et al. 2020). For example, Staver et al. (1995) show increased P at the soil surface with no-till farming, resulting in increased dissolved P in overland flow. In contrast, conservation till practices can decrease dissolved P in runoff and reduce P concentrations by lightly disturbing the soil surface and leaving at least 30% crop residue cover (Thomason et al. 2016; Pickford 2022).

Table 4.9. Annual mean cropland area (km^2) of tillage management types (Source: Thomason et al. (2016) and Pickford (2022)) in the Greensboro watershed between 1989 and 2021. Source: Figure 2.4.

Tillage category name	Residue cover	Mean Cropland Area 1989-2013	Mean Cropland Area 2014 - 2021	Units
Conventional or high tillage, Inversion	<15% cover or 15-29% cover with full width tillage			
High residue	≥60% cover, minimum soil disturbance	19 ± 0.8	51 ± 2.3	km^2
Conservation tillage or low till	30-59% cover	4.7 ± 0.62	37 ± 2.2	km^2
		1994-2013	2018 - 2021	
No-till, Strip-till, or Low residue	15-29% cover, strip-till or no-till, and less than 40% soil disturbance	7.1 ± 0.7	25 ± 0.09	km^2

Farmers applied high residue, conservation, and low residue (no-till) tillage practices on nearly all croplands in the Greensboro watershed between 2014 and 2021 (Fig. 2.4). Before 2014, tillage management practices were infrequently applied or not reported. Most croplands were under high residue or conservation tillage practices between 2014 and 2021 (Table 4.10). After 2018, high tillage and conservation tillage practices significantly decreased as low residue (no-tillage) increased ($p \leq 0.05$). Low residue (no-tillage) leaves 15 – 29% of crop residue, less than 40% soil disturbance, and can result in increased dissolved P in overland flow (Staver et al. 1995).

Even though tillage practices were commonly implemented in the Greensboro watershed, these attempts to minimize soil erosion and P loss appear insufficient to counter P concentrations that continue to increase in local streams (Fisher et al. 2006b; Langland et al. 2013), and these findings are in agreement with Fanelli et al. (2019) and Pisani et al. (2020). A recent study by Fanelli et al. (2019) found that manure applications and conservation tillage correlated with changes in P concentrations at high flow, suggesting that these activities could increase P concentrations and partially explain increasing P export at the USGS gauge. Additionally, more applications of low residue (no-tillage) practices in the Greensboro watershed increase the potential for dissolved P in overland flow (Staver et al. 1995). More applications of low residue tillage could partially explain the increasing P export measured at the USGS gauge. However, modeled P concentrations and yields decrease with other agricultural BMPs (Figs. 4.5 and 4.6), and this suggests that the amount of high residue and conservational tillage practices may have been overestimated (efficiencies are correct), their efficiencies are overestimated (amount is correct), or the overall impact of increasing dissolved P from increasing low residue tillage practices is minimal. Thus, further research is needed to understand the impacts of conservation tillage practices and low residue (no-till) practices in manure surplus areas.

4.5.3 Intensive agriculture

To ensure food production meets the demands of a growing human population, the mechanization of crop production, agrochemical use, irrigation, and improved drainage have allowed for an unprecedented increase in crop yields, with cereal yields rising by a factor of two to three in the United States and Europe since 1950 (Howden et al. 2013). More specifically, intensive agricultural practices apply large amounts of fertilizer (>200 kg N ha^{-1}) to maximize yield and profits from a smaller area of land (Congreves et al. 2015). However, cropland application of manure based on N content results in soil P above plant needs (Qin et al. 2018), and high N fertilizer applications can increase N loss via denitrification, volatilization, leaching, runoff, and erosion (Congreves et al. 2015). For example, the application of 9 tons ha^{-1} of broiler litter, a standard rate often used to meet crop N needs, provides approximately 270 kg N ha^{-1} and 100 kg P ha^{-1} (Bolan et al. 2010). Depending on crop N and P needs, applications based on crop N needs can result in soil-P accumulation. Consequently, during intense storm events, overland flow carries sediment into streams, and any P-bound sediment enters the stream and can degrade water quality over time (Staver et al. 1995; Fisher et al. 2006b; Ator et al. 2015; Fanelli et al. 2019). Empirical studies have shown that the legacy P combined with annual manure N application rates leads to soil-P saturation, preventing any further retention of applied P and subsequent increases in P export (Ator et al. 2011; Fertig et al. 2014; Qin et al. 2018; Kleinman et al. 2019). In the following sections, I explore three aspects of intensive agriculture: manure surplus, animal feed, and nitrogen use efficiency.

Manure surplus

Challenging problems associated with livestock manure utilization are widespread due to fewer, larger, and more spatially concentrated animal feeding operations with increasing numbers of livestock, notably in the United States, Europe, and China (Lassaletta et al. 2013; Svanback et al. 2019; Zou et al. 2020). Spatially concentrated livestock operations worldwide have been linked to greenhouse gas emissions (Glibert 2020), groundwater contamination (Rosa et al. 2018), and frequent instances of eutrophication in South America, China, Europe, and the United States (Rosa et al. 2018; Wang et al. 2018; Svanback et al. 2019; Glibert 2020; Zou et al. 2020). Moreover, as livestock production becomes more spatially concentrated, the amount of manure nutrients for cropland application relative to the assimilative capacity of cropland available often exceeds the individual farmland's ability to assimilate applied manure N and P (Kellogg et al. 2014).

The long history of poultry manure application to croplands in the Chesapeake Bay watershed is well-documented, and research shows this has resulted in soil-P saturation, particularly in Delmarva (Ator et al. 2011; Tiessen et al. 2011; Fertig et al. 2014; Zhang et al. 2023). Figure 11 shows slight increases in the land area receiving manure within the Greensboro watershed tri-county region comprised of Kent County, Delaware, and Queen Anne's and Caroline counties in Maryland. Yet, there is still insufficient agricultural land to apply large quantities of manure at lower application rates (NRCS 2003). Additionally, more manure remained in the tri-county region as manure transported outside of the region remained unchanged, animal waste management practices nearly doubled, and applications of manure injection and incorporation practices were rising. These findings are consistent with Keisman et al. (2018) and Chang et al. (2021), and the CAST data indicate manure N application rates in 2021 increased by 40%, and manure P application rates increased by 50% since the TMDL (Fig. 4.9). Program managers should incentivize the research and development of additional manure recycling products.

Animal feed

The separation between crop production for food and animal feed and agglomerations of large-scale livestock and poultry operations are important drivers of N and P surpluses in many parts of the world and contributes to eutrophication (Lassaletta et al. 2013; Wang et al. 2017a; Svanback et al. 2019). Between 1961 and 2011, confined livestock production systems were supported by imported soybean and maize grown in a few countries, such as the United States, Argentina, and Brazil (Wang et al. 2017a). Furthermore, the major livestock-producing states in the United States imported more than 80% of their animal feed in 1995 (Sharpley 1999) because the magnitude of livestock and poultry in these animal concentrations greatly increases the demand for animal feed, which far exceeds the local supply (Brown et al. 2020). Additionally, the largest watershed in North Carolina, Cape Fear River, has one of the highest concentrations of swine and poultry confined animal feeding operations worldwide and imports over 90% of soybeans for animal feed (Brown et al. 2020). The magnitude of livestock and poultry production requires a large volume of animal feed, mainly soybean and cornmeal, which exceeds the grain volume that local farmers can supply (Beegle 2013), even if the majority of locally grown corn and soybean (e.g. in Delmarva) is dedicated to the poultry industry (Staver 2001; Fisher et al. 2006a; Ator et al. 2015).

Animal feed imports to the Mid-Atlantic states are a relatively low-cost option and facilitate the growth of large animal feeding operations in North Carolina and other livestock and poultry clusters across the United States (Brown et al. 2020). Consequently, animal feed imports transfer N and P in the animal feed from grain-producing areas to animal-producing areas, increasing external, “new,” N and P influxes to nutrient-enriched watersheds and resulting in soil-P accumulation (Sharpley 1999; Brown et al. 2020). For example, animal feed without phytase treatment results in only $^{1}/_{3}$ of the P efficiently used by the animal, and the remaining $^{2}/_{3}$ of P leaves the animal via excrement (Sharpley 1999; Sharpley et al. 2006; Sharpley et al. 2010; Beegle 2013). Improvements to efficiently use nutrients in animal feed are needed to lower the amount of “new” N and P influxes to watersheds.

Nitrogen use efficiency

Studies show that as fertilizer applications increase globally, the global N use efficiency (NUE), defined as the percent of applied N fertilizer removed by harvested crop products (Cassman et al. 2002), decreased from 68% in the early 1960s to 42% by 2010 (Erisman et al. 2011; Lassaletta et al. 2014; Zhang et al. 2015b). Swaney et al. (2018) showed NUE ranges from 40-60% on average when N fertilizer is approximately 25% to 60% of the total N inputs (sum of fertilizer N, N fixation, atmospheric N, and manure N). Empirical research conducted by Cassman et al. (2002) showed that the average fertilizer N uptake of corn grown in the U.S. is < 40%. In a more recent study, Swaney et al. (2018) indicates NUE decreased across the United

States from 49% in 1987 to 1997 to 45% between 2002 and 2012 due to crop production not increasing as fast as higher applications of N fertilizer, sometimes above crop N requirements, resulting in unused N in the field.

Higher N fertilization rates are designed to increase crop yields but also appear to increase unharvested N. Conceptually, if crop yields do not increase linearly with N applications, the corn nitrogen use efficiency (NUE) must be <100%. Figure 4.14 is a conceptual model showing commonly observed corn NUE based on hyperbolic responses of corn yield to fertilizer additions. Swaney et al. (2018) showed that declining NUE could reflect an imbalance between manure inputs and cropland area (Fig. 4.11) and that the NUE of major crops grown in the U.S. between 1987 and 2012 generally decreased over time due to the increasing use of fertilizer N above crop N requirements. Lu et al. (2019) assessed corn NUE response to N fertilizer use across the US and found similar results in which corn NUE begins to decline when the N fertilization rate exceeds 150 kg N ha^{-1} y^{-1}.

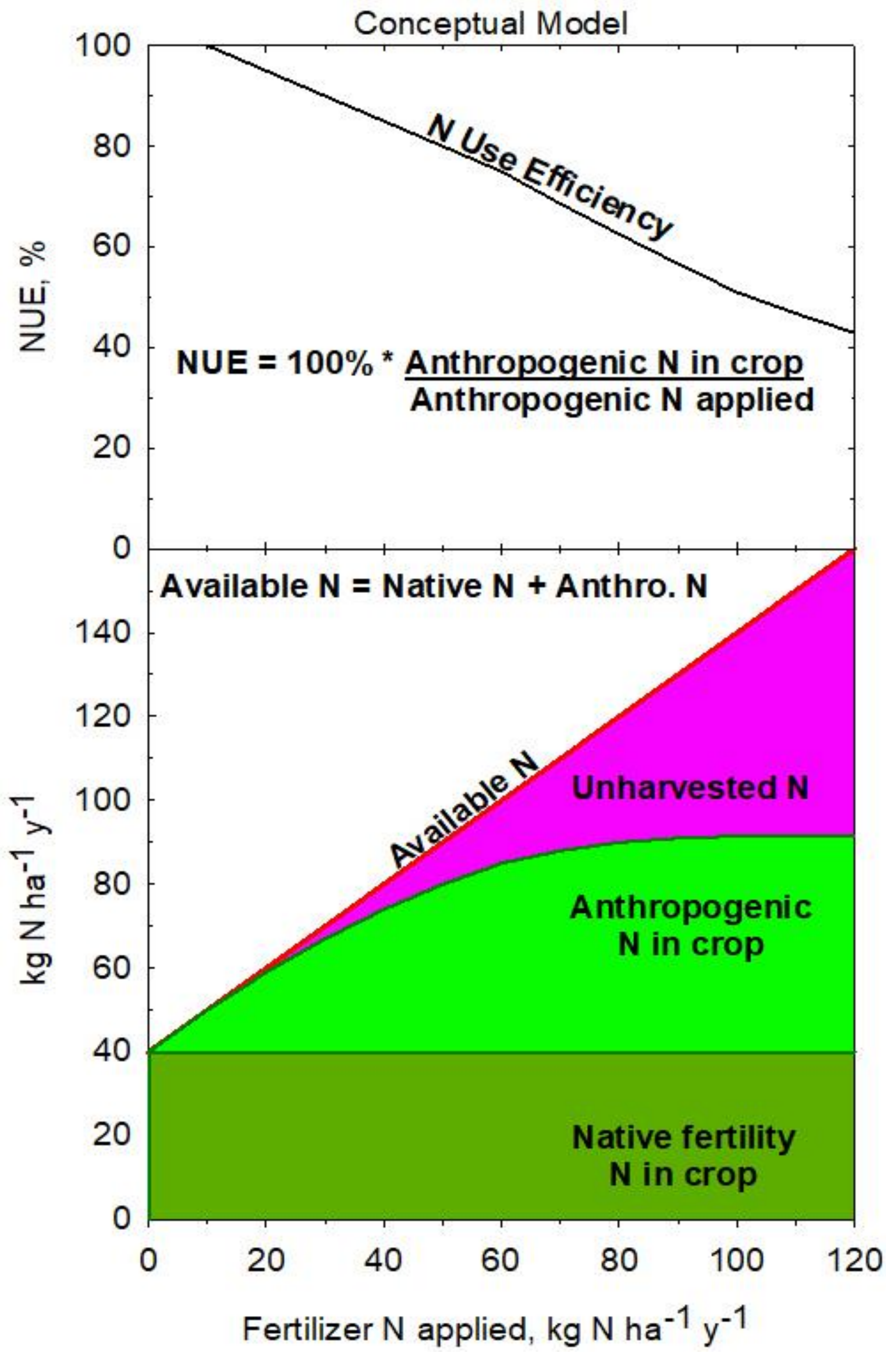


Fig. 4.14. Nitrogen use efficiency model based on the commonly observed hyperbolic response of corn yields to N applications (Fisher, pers. com.)

Despite lowered NUE, farmers apply additional N fertilizer to relatively small areas of croplands in Delmarva to produce higher crop yields of corn (J. Lewis, Uni. of Maryland, pers. com.). The N fertilization rates for corn (starter plus side-dress) are currently around 213 kg N ha^{-1} y^{-1} (190 lbs N ac^{-1} y^{-1}) for dryland farming in Caroline County, Maryland and increase in the northern counties on the Delmarva Peninsula and for irrigated croplands (J. Lewis, Uni. of Maryland, pers. com.). A partial balance on corn fields in Delmarva is illustrated in Figure 4.15 and estimates approximately 50% NUE by corn, which is 5% higher than most recent corn NUE suggested by Swaney et al. (2018). Due to climate change, the growing season has lengthened in Delmarva, and most of the state of Maryland has experienced warmer temperatures and frequent, heavy storm events (USEPA 2016); hence, favorable growing conditions for farmers. The favorable growing conditions contribute to increasing corn fertilization rates and have reportedly yielded more bushels of corn. Thus, farmers expect to increase corn fertilizer rates further to achieve higher corn yields, consistent with the historical trend of increasing fertilizer N rates between 1985 and 2021 shown in Figure 4.12a. Corn NUE should be measured to accurately reflect the corn N uptake in today's climate under higher fertilizer N rates.

Climate change and the inefficient use of applied N and P threatens coastal waters and jeopardizes global crop production and food security as the human population grows (Howden et al. 2013; Yuan et al. 2017). For example, future climate change will cause greater NUE reductions in northwest China (wheat: 43%; maize: 34%) than in the northeast (maize: 4%), which increases N losses to the environment (Liang et al. 2019). Liang et al. (2019) also show maize and wheat yields in northwestern China decrease by -31% and -16%, respectively, and slightly increase by 6% in northeastern China. The results demonstrate the risks of future climate changes on crop yield and NUE in China and are concerning due to their impact on future food security in one of the world's most populous countries (currently 1.4 billion per United Nations). Furthermore, manure application had higher crop NUEs (wheat: 6.66–31.27%; maize: 23.82–68.19%) and N uptakes than other fertilization treatments under future climate change (Liang et al. 2019). The results help target fertilization practices for effectively mitigating climate change. However, further research is required to investigate the impacts on water resources in future climate change scenarios where increasing manure applications are prevalent. Also, models are needed to investigate the crop NUE in areas of intensive livestock production and the ecological impacts on water resources in an uncertain future climate.

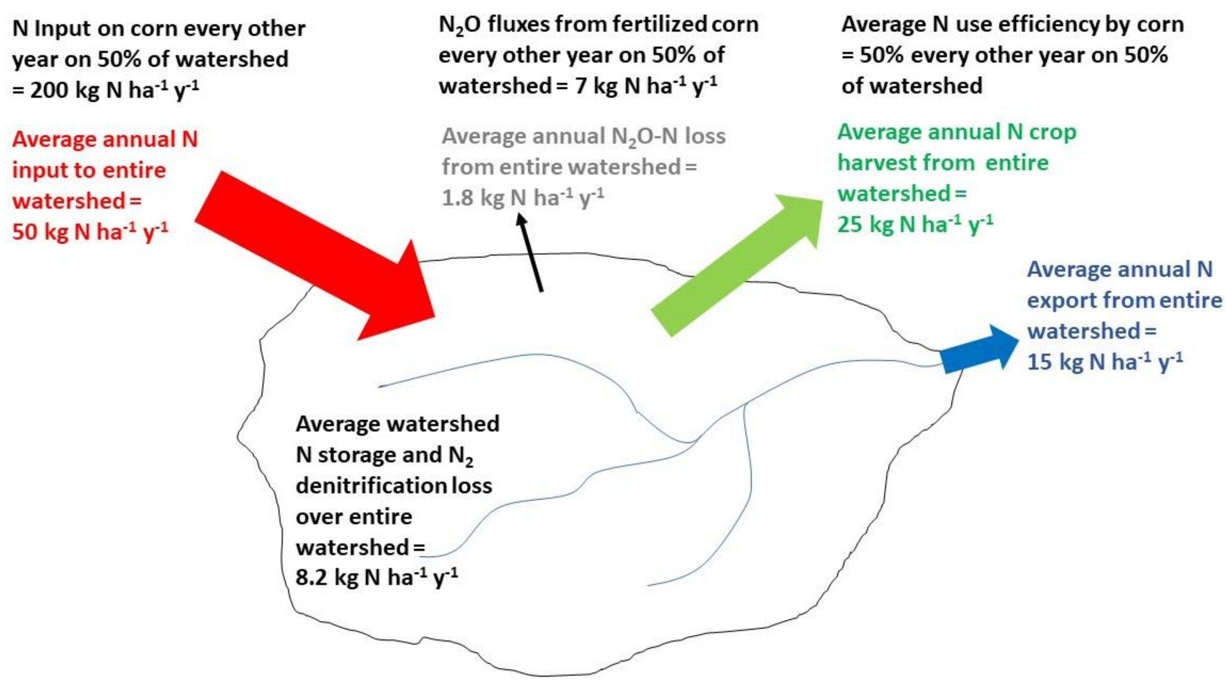


Figure 4.15. Partial balance on corn fields in Delmarva (Fisher, pers. com.).

4.5.4 Model parameters

A review of agricultural BMP effectiveness models conducted by Xie et al. (2015) indicates that modeling methods are spatially and temporally scale-dependent. For example, remotely sensed spatial data are used to assist with monitoring of implemented conservation practices and predict water quality response at the watershed scale in the United States, Europe, and China (Huang et al. 2012; Atzberger et al. 2013; Rigge et al. 2014; Thieme et al. 2020). In the United States, the Maryland Department of Agriculture administers the statewide cover crop cost-share program, and a collaborative effort with the United States Department of Agriculture-Agricultural Research Service and the U.S. Geological Survey has developed satellite remote sensing techniques based on 30-meter resolution imagery to measure cover crop performance statewide (Thieme et al. 2020). However, statewide cover crop area measurements based on coarse spatial resolution data could overestimate cover crop implementation in smaller watersheds (Dark et al. 2016). Additionally, overestimating cover crop implementation can result from remotely sensed measurements that cannot distinguish traditional cover crops (unfertilized) from commodity cover crops (fertilized and harvested for profit). Consequently, the BMP efficiencies may be overrated, and predicted water quality responses may be optimistic.

High and low resolution spatial data affects water quality goals and management recommendations. For example, the Chesapeake Bay load reduction goals are based on the bay-level model, which uses coarse spatial data (Amin et al. 2020). However, Amin et al. (2020) suggest that higher resolution spatial data should replace coarse spatial resolution data if regulatory plans, such as total maximum daily loads, are developed, primarily because coarser resolution spatial data cannot consider the heterogeneity in local conditions, which affects BMP effectiveness. For example, one of the unique cropland characteristics on the Delmarva Peninsula is the extensive network of drainage ditches that maintain low water tables to permit agricultural land uses, and studies have shown drainage ditches alter nutrient flow paths (Fisher et al. 2006a; Needelman et al. 2007; Carstensen et al. 2020). The agricultural diches are concerning because nutrient transport via groundwater and overland flow during storm events to these artificial drainage ditches bypass natural flow pathways and could be exacerbated in intensive agricultural areas (Sharpley et al. 2006; Kleinman et al. 2007; Needelman et al. 2007; Schmidt 2007; Carstensen et al. 2020). Moreover, Amin et al. (2020) demonstrate the potential use of watershed models using finer spatial data in central Pennsylvania to improve recommendations for BMP implementation under the Chesapeake Bay TMDL. Models should incorporate high resolution spatial data for smaller watersheds to improve load reduction recommendations and water quality response in parallel with BMP implementation. In turn, the basis of regulatory plans should be finer-scale spatial data instead of coarser data.

Additionally, Sowa et al. (2016) coarse-grained analyses suggest water quality improvements due to implementing conservation practices in agricultural watersheds in the Great Lakes Region. Yet, finer-grained analyses predict persistent water quality impairments even as 50% of the agricultural lands are treated with management practices. The results show coarse-grained analyses could significantly underestimate the scope of the solution needed to address these impacts in stream ecosystems (Sowa et al. 2016). In a recent modeling study by Hashemi et al. (2018), findings were consistent with Sowa et al. (2016) in that the use of finer-scale data resulted in improved estimates of N load reductions from agricultural catchments in Denmark if estimates were based on large map scales compared to using sub-catchment maps (i.e., small map scale). Depending on applications of the remotely sensed cover crop area, remotely sensed cover crop data may need supplemental validation by on-the-ground measurements and comparisons to reported areas planted by farmers.

Modeled outcomes consistently overestimate the effectiveness of conventional nonpoint source best management practices (Stephenson et al. 2021). For example, (Hively et al. 2020) modeled ten years of consecutive cover crop applications, and results indicate N efficiency increased in subsequent years (Fig. 3.7a). However, as BMPs age, their nutrient removal capacity will likely change regardless of maintenance because structures wear down and, in some cases, pollutants accumulate (Liu et al. 2017b). Although long-term empirical cover crop studies are limited, the results by Staver et al. (1998) demonstrated N efficiencies gradually declined each year after nine consecutive years of cover crop growth due to the depletion of soil N inventories and groundwater N concentrations (Fig. 3.7c). Liu et al. (2017b) also found that the water quality impacts of BMPs implemented at the watershed scale have not been as rapid or large as expected, possibly due to overly high expectations for the BMPs' long-term efficiency. Additionally, Silaphone (Dissertation Chapter 3) shows the cover crop mean N efficiencies of modeling studies are significantly higher than empirical cover crop mean N efficiency. Therefore, models should reflect empirical BMP efficiencies and modify annual efficiencies over their lifespan due to the natural deterioration of BMPs, regardless of maintenance.

Nonpoint source loads and BMP efficiencies are variable, but modeling generates constant levels of N removal over the entire BMP lifespan, contradicting on-the-ground outcomes (Liu et al. 2017b; Stephenson et al. 2021). For example, rooted within CAST are delivery factors representing the proportion of nutrient field losses transported via streams and rivers to the tidal portion of the Chesapeake Bay. The delivery factors are fixed, even though these factors account for variable nutrient and sediment processes, such as nutrient losses due to denitrification, floodplain or reservoir deposition, and stream bank erosion, that decrease and increase nutrient and sediment export (Table 4.10). The percentage of nutrients exported downstream from the Greensboro watershed to the bay is affected by delivery factors that systematically reduce TN (52%), and much of the calculated TN exported from land to surface waters is reduced by up to 25%. Stream-to-river delivery factors also assume that TP reductions (up to 27% to 46%) occur 100 % of the time, increasing the discrepancy between CAST modeling and USGS calculations. Consequently, overestimating the water quality response in parallel with BMP implementation is likely in the Greensboro watershed. Nonetheless, constant nutrient reduction credits achieve TMDL compliance (Stephenson et al. 2021). However, modeling actual in-stream processing may be challenging unless other environmental processes, such as the annual manure applications on saturated croplands resulting in N and P groundwater and overland flows, are considered (Sith et al. 2019).

Table 4.10. Percentage of nutrient export transported from land to surface waters. Abbreviations: “Transport” represents the proportion of nutrients delivered downstream (delivery factor) and the percentage of nutrient reduction, “Land to Water” represents the percent of TN and TP export from the land to first and second-order streams where “*” originates from permitted and non-permitted feeding spaces and “**” originates from other agricultural land uses., “Stream to River” represents the percent of TN and TP export from first and second-order streams to the main steam, and “River to Bay” represents the percent of TN and TP export from the main stem to the tidal edge of the Bay.

Nutrient	Transport	Nutrient from Land to Water	Nutrient from Stream to River	Nutrient from River to Bay
TN	Delivery factor	0.75 – 1.04	0.81 – 0.89	0.48
	Reduction %	0 to 25	11 - 19	52
TP	Delivery factor	*0.08 – 0.10 **0.75 – 0.84	0.54 – 0.73	0.89
	Reduction %	*90 – 92 **16 - 25	27 - 46	11

4.5.5 Climate change impacts agricultural mitigation efforts

Global average temperatures have risen since the 1950s (Lobell et al. 2011), and increasing air temperatures and changes in precipitation patterns and intensity are anticipated throughout the U.S. over the 21st century (Melillo et al. 2014). Anthropogenic climate change has likely contributed to increased global average precipitation over land since 1950, with a faster rate of increase since the 1980s (Masson-Delmotte 2021). Additionally, applications of simple linear regression by Rice et al. (2017) project watersheds north of the Pennsylvania-Maryland state border will have higher annual mean discharge in 2025, the target date for implementing the Chesapeake Bay TMDL, and this is in agreement with the annual average discharge increases measured at the USGS gauging station in Greensboro watershed (Fig. 4.1).

These changes in precipitation are expected to increase riverine TN within the continental United States (Renkenberger et al. 2017; Sinha et al. 2017). Moreover, Schmidt et al. (2019) and Giri et al. (2020) predict a rise in streamflow and surface runoff and increases in agricultural source loads of sediment, nitrogen, and phosphorous under future increases in temperature and precipitation. However, in a recent study, Ator et al. (2022) show a slight net decline in annual N export to the Chesapeake Bay between 1995 and 2025 due to increasing rates of denitrification, ammonia volatilization, and changes in plant phenology that offset a wetter climate. Conversely, empirical field measurements of N export from Chesapeake Bay tributaries draining the Delmarva Peninsula show increasing TN and phosphate (Fisher et al. 2021). Moreover, a recent modeling study by Bhatt et al. (2023) shows climate change will increase streamflow (2.3%–6.2%), nitrogen (2.6%– 10.8%), phosphorus (4.5%– 26.7%), and sediment (3.8%– 18.8%) loads to the Chesapeake Bay.

There is a growing scientific consensus on climate change and its impact on agricultural mitigation efforts to abate anthropogenic eutrophication because the N and P reduction goals needed to achieve water quality and the BMP efficiencies measurement of pollutant removal performance are generally based on historical climate (Schmidt et al. 2019). For example, Schmidt et al. (2019) model prediction shows BMPs in the United States Midwest and Coastal Plain continue to reduce nutrient export, but BMP removal efficiencies decline due to more intense runoff events, biological responses to changes in soil moisture and temperature, and intensified upland nutrient losses. Moreover, Renkenberger et al. (2017) modeling results suggest that in the U.S. Northeast, BMPs designed to remediate water quality problems under the current climate will be insufficient to maintain water quality with climate change. The model predictions by Giri et al. (2020) support Renkenberger et al. (2017) findings. In turn, Giri et al. (2020) suggest that the nutrient removal capabilities of cover crops, filter strips, and no-till could negate the climate change impact on water fluxes and water quality in Southern New Jersey with more widespread implementation. In response, BMPs must be more widespread, and in some cases, existing BMPs must redesigned to adapt to climate change impacts.

4.6 Agronomic recommendations

The agronomic management practices recommendations are responses to problems caused by anthropogenic land uses. The suggestions below do not address anthropogenic N and P inputs that are likely to continue at current application rates and, in some cases, higher rates. In addition to the recommendations below, I recommend the agricultural community, policy-makers, program managers, and research scientists candidly discuss acceptable water pollution levels given continued nutrient inputs and come to terms with realistic expectations for a healthy waterbody (Beegle 2013; Lucas et al. 2021).

- Develop efficient manure recycling approaches within the local agricultural systems via nutrient management practices and explore decreasing manure applications on cropland where soil P > 100 mg kg^{-1} (Beegle 2013; Lucas et al. 2021)
- Establish a formal manure marketplace for sellers and buyers that can also offset the costs of transporting manure from areas of surplus to deficit areas (Sharpley et al. 2006; Bolan et al. 2010; Spiegal et al. 2020)
- Further research is needed to understand the combined impacts of soil-P saturation and tillage practices.
- Enforce nutrient management plans to ensure practices are followed (Staver 2001).
- Further research and development are needed to explore alternative uses of manure, including composting, methane/energy generation, and granulating/pelletizing (Sharpley et al. 2010; Lim et al. 2023).

4.7 Modeling recommendations

Modeling and empirical measurements are needed to disentangle multi-layered and often interrelated factors contributing to eutrophication in complex ecosystems, such as the Chesapeake Bay, Baltic Sea, Gulf of Mexico, and other basins. However, program managers must choose the appropriate model given the modeling capabilities, such as assessing multiple environmental variables (Xie et al. 2015). Program managers must also understand the limitations of modeling results (Liu et al. 2017b) and subsequent applications policy development, estimating BMP effectiveness, or targeting locations for BMPs (Sith et al. 2019; Amin et al. 2020; Stephenson et al. 2021). Below, I offer recommendations to improve modeling efforts.

- Improve CAST output with more validation from USGS observations.
- WRTDS flow normalization is based on the concept that there are large and random interannual variations around an unchanging mean discharge. Investigate whether the interannual increases in mean discharge observed at Greensboro invalidate the use of flow normalization (Fig. 4.1).
- Adjust N and P efficiencies to reflect the lifespan of cultural and structural BMPs.
- Incorporate nutrient transport via artificial drainage ditches that bypass natural flow pathways and exacerbate N and P transport (Sharpley et al. 2006; Kleinman et al. 2007; Needelman et al. 2007).
- Factor soil-P accumulation and subsequent soil-P saturation due to annual manure applications, resulting in particulate and dissolved P export via groundwater and overland flows (Sharpley et al. 1994).
- Improve modeled P output due to increased import of animal feed (Sharpley et al. 1994; Sharpley et al. 2006; Bolan et al. 2010).

Chapter 5: Synthesis

5.1 Introduction

Eutrophication is a well-documented water quality response to over-enrichment by nitrogen (N) and phosphorus (P) in fresh, estuarine, and coastal waters from nonpoint sources and point sources (Boesch 2001; Kennish 2002; Kemp et al. 2005; Howarth 2008; Schindler et al. 2008; Smith et al. 2009; Lankoski et al. 2013; Foucher et al. 2020; Malone et al. 2020). Agricultural best management practices (BMPs) are the primary tool for controlling eutrophication in rural areas, particularly in the Chesapeake Bay watershed, where BMPs are vital to achieving TMDL goals (Boesch 2006). However, local water quality in the headwaters of the Choptank River (Fig. 1.1) has not improved despite implementing BMPs (Fox et al. 2021). Thus, further investigation of agricultural BMP effects on water quality in the Greensboro watershed is needed (Fig. 1.3).

My overarching research question is, "Why have N and P export increased between 1970 and 2021 if agricultural BMPs were implemented?" The water quality record also shows brief interannual variability in N and P concentrations and suggests that at least one of the following is true:

1) There is **insufficient** BMP implementation at the field scale or watershed scale.
2) BMPs are **malfunctioning** due to improper installation or lack of maintenance.
3) The BMPs are **overwhelmed** by anthropogenic N and P inputs.
4) Implemented BMP effects are **masked** due to legacy nutrients or nutrient time lags.
5) The BMP efficiencies are **overestimated** at the field scale or watershed scale.

My research examines the above possibilities. To test the overarching research question, I applied statistical approaches to three linked, testable hypotheses to systematically evaluate agricultural BMPs and their impacts on nutrient (N and P) export from the Greensboro watershed. In the following discussion, the outcome of each testable hypothesis is summarized, and a synthesis of factors is provided.

5.2 Chapter 2

My first hypothesis was that agricultural BMPs have increased significantly in the Greensboro watershed. To test this hypothesis, I compiled publicly available data via the Chesapeake Assessment Scenario Tool (CAST) and estimated the subsequent edge-of-stream N and P export.

5.2.1 Best management practices implementation

Between 1985 and 2021, 133 unique varieties of BMPs were installed in the watershed. Implementation of BMPs in the Greensboro watershed targeted nonpoint pollution sources in the agricultural (98), rural-urban development (23), septic system (5), animal (4), and natural (3) sectors. In this section, I report important findings on selected agricultural BMPs, including cropland BMPs and BMPs applied to livestock and poultry. Cropland BMPs, such as annual **cover crops** (Fig. 2.4d), **manure incorporation or injection** (Fig. 2.4e)**, and soil tillage practices** (Fig. 2.4 g-i), increased significantly post-TMDL. For example, traditional cover crops (unfertilized, no spring harvest) increased 7.25 times ($p < 0.001$). Commodity cover crops (fertilized in March, harvested in June) increased 4-fold ($p = 0.004$). Similarly, annual tillage practices that achieve crop residue of at least 60% (high residue, Fig. 2.4g), 30 -59% (conservation, Fig. 2.4h), or 15-29% (low residue, Fig. 2.4i) on the soil surface immediately after planting increased significantly ($p < 0.001$, Table 2.5). However, after 2018, high tillage and conservation tillage practices significantly decreased as low residue (no-tillage) increased ($p \leq 0.05$). Low residue (no-tillage) leaves 15 – 29% of crop residue, less than 40% soil disturbance.

After the TMDL, annual nutrient management plans (Fig. 2.5a) covered 8.6 times more area ($p < 0.001$, Table F4). Annual nutrient management plans continued to increase post-TMDL and at a yearly rate more than five times greater than pre-TMDL. Annual nutrient management plans prescribe the placement, rate, and timing of N and P fertilizer and BMPs applied to croplands. Additionally, newly implemented practices where manure was injected into the soil immediately or incorporated over 1-3 days occurred shortly after the TMDL. This data establishes increasing nutrient inputs via manure injection and demonstrates significant implementation of required nutrient management plans. Additionally, the increased amount of cover crops used in CAST modeling is concerning because Chapter 3 showed that modeled cover crop N efficiencies are overestimated and could overestimate progress toward improved water quality in the Chesapeake Bay and other regions.

In the Greensboro watershed, efforts to transport poultry manure from a Greensboro watershed county (Caroline, Queen Anne, and Kent counties) to other counties decreased post-TMDL (Figs. 2.6, panels e and f, Table F5). In contrast, there were significant increases in the number of animal units (e.g., 1 A.U. = 125 adult chickens or a 454 kg cow) affected by animal waste management practices (Fig. 2.6d) post-TMDL ($p < 0.001$, Table 2.6). Post-TMDL, additional animal waste management practices stored broiler and poultry waste, averaging 87,374 ± 4,661 animal units per year, an increase of 2.7 times greater than pre-TMDL uses.

Unfortunately, animal waste management practices do not reduce nutrients but attempt to move and apply the manure elsewhere. The data indicates more manure remained within the Greensboro watershed counties, as manure transport remained unchanged and animal waste management practices nearly doubled (Figs. 2.6, panels d-f, Table 2.6). These findings are consistent with Keisman et al. (2018) and Chang et al. (2021). Chapter 4 discusses the effects of increasing animal waste management practices on nutrient input and export.

5.2.2 Nutrient export

The data shown in Figure 2.7 indicates agricultural land-based BMPs resulted in significant N (Fig. 2.7a) and P (Fig. 2.7b) edge-of-stream nutrient reductions between 1985 and 2021 ($p < 0.0001$). Still, nutrient export in 2021 from the agriculture sector was far greater than those from the rural-urban development sector (Fig.2.7). Compared to agricultural nutrient export in 2010, BMP implementation in 2021 resulted in no significant changes in N export and P export increased 2% after BMP implementation (Table 2.8). These results agree with Fisher et al. (2021), where the agriculture sector contributed little to water quality improvement in the Choptank River basin. Overall, moderate water quality in the Choptank River basin is comparable to the Lower Eastern Shore, Patuxent, Patapsco and Back, and Lower Susquehanna drainage basins in the Chesapeake Bay watershed (IAN 2023). Poorer water quality was detected in the Upper Eastern Lower Western Shore basins north and south of the Choptank River basin. Only the Upper Western Shore and Lower Potomac reportedly have better water quality than the Choptank River, as reported in the recent Chesapeake Bay & Watershed Report Card (IAN 2023). These results indicate (1) that the increased number of functioning BMPs are overwhelmed by current nutrient inputs to the Greensboro watershed and other drainage basins within the Chesapeake Bay watershed, (2) that BMP efficiencies could be overestimating nutrient reduction, and (3) that there are insufficient quantities of BMPs suited to the natural environment in the watershed, which limit reaching the local TMDL goals of reducing N and P by 24% and 18%, respectively.

5.2.3 Test of hypothesis 1

My findings indicated that the number of BMPs in the agricultural sector increased significantly between 1985 and 2021, supporting the hypothesis that BMP implementation has increased significantly in the Greensboro watershed between 1985-2021.

5.2.4 Agronomic recommendations

This study used CAST to acquire BMP implementation in the Greensboro watershed and CAST-modeled nutrient export predictions. With this improved access to BMP implementation and nutrient data, decision-makers can consider adaptive management measures to decrease nutrient export downstream. These measures may include the following:

- Higher payments are needed to incentivize the installation of BMPs suited to hydrogeomorphology in the Greensboro watershed.
- Develop outreach programs to gain community support for widespread agricultural BMPs.
- Allocate BMP funding in TMDL segments having to reduce nutrient export by a significant percentage, such as the 76% N reduction needed in the CHOTF to achieve the land-based load allocation.

- Explore manure management options, including reducing manure N and P applications onto agricultural cropland, applications of supplemental manure onto alternative vegetative covers outside the agriculture sector, and publicly funded manure transport programs to immediately remove manure from surplus areas to deficit areas.
- Research is needed to understand how to adapt existing BMPs and future BMPs to a changing climate.
- Explore BMP nutrient removal performance and if the efficiencies are adequately tested.
- Research is needed to explore factors influencing modeled N and P nutrient export and nutrient export based on field measurements.

5.3 Chapter 3

My second hypothesis was that agricultural BMPs have an adequate basis for estimating their capacity to reduce N export. To test this hypothesis, I conducted a meta-analysis on 689 cover crop (CC) N efficiencies reported in 18 empirical and modeling studies in the US Coastal Plain province published between 1980 and 2022. This cover crop assessment (1) identified multiple N efficiency calculation approaches, (2) quantified cover crop N efficiencies, (3) summarized common variables identified in the literature that influenced the reported cover crop N efficiencies, and (4) identified limitations that may have impacted cover crop N efficiencies.

5.3.1 The basis of cover crop N efficiencies

The experimental approaches included control versus treatment (CT) in parallel measurements in two areas, and before and after (BA) in serial measurements in one area. Both are used in empirical and modeling studies observing combinations of N loss pathways normalized by N inputs (Table 3.12). By 2007, observational field-based research methods began transitioning from BA immobilization studies to CT experiments observing N loss pathways, such as groundwater N export, overland flow, soil N inventories, or multiple direct pathways (i.e., lateral flow, overland flow, and groundwater export). The cover crop N efficiency was calculated as the ratio of an N interception by cover crop biomass or a reduction in soil or groundwater N divided by an N input, e.g., previous spring fertilizer or a previous soil or groundwater N concentration or flux. These variables used in empirical and modeling experimental approaches resulted in wide ranges in mean cover crop N efficiencies. For example, empirical BA experiments resulted in N efficiencies ranging from 7-71% (Table 3.9a), and CT experiments used in empirical and modeling studies widely range from 16-86% (Table 3.9b). Mean group comparison tests indicate higher N efficiencies are associated with the following: model > empirical methods, CT > BA experiments, and soil N > all other N pathways and N inputs ($p < 0.001$). However, the history of published cover crop studies (Table 3.1, Fig. 3.3) indicates a preference for empirical or modeled CT groundwater N export experiments, which could bias cover crop N efficiencies and have a much larger impact on water quality model outcomes. The CT experimental approach is subject to spatial variations within the same year.

Empirical cover crop studies in the Coastal Plain have not demonstrated a consistent methodology to estimate cover crop N efficiency but instead adapt BMP efficiency calculations (Table 3.2a, 3.2b) to observed variables. For example, statistical tests of the results of BMP efficiency indicated that cover crop N efficiencies based on spring soil N inventories are significantly greater than N immobilization (<0.001, Fig. 3.12) and groundwater N export

(<0.001). Representing cover crop N efficiencies via groundwater and soil N inventory experiments can produce higher N efficiency outcomes than immobilization studies. These effects on N efficiencies mean agreement among researchers is needed to define cover crops' N efficiency in ways that do not limit or confound experimental results based on observed multiple N loss pathways.

One of the key findings of this research is that the empirical mean N efficiencies of barley (69 ± 3.5, $p < 0.001$) and wheat (59 ± 4.1, $p = 0.002$) cover crops are significantly greater than the mean N efficiencies of cereal rye cover crops (44 ± 2, Tables 3.16, 3.19). These findings conflict with well-established cover crop mean N efficiency values in the Coastal Province of the Chesapeake Bay watershed, where the traditional wheat cover crop N efficiency ranges from 11 to 31% and is lower than the traditional cereal rye cover crop N efficiency range of 16 to 45% (CBP 2020a). The disproportion between the mean N efficiency of wheat from the cover crop literature and the accepted standard used in the Chesapeake Bay watershed partially explain the variables used to calculate wheat N efficiency. On the one hand, winter wheat N efficiencies were based on observations of N pathways, such as soil N inventories and N immobilization, normalized by the previous fall soil residual N. On the other hand, cereal rye N efficiencies were based on N immobilization normalized by the previous spring fertilizer N. Comparison tests demonstrated that rye N efficiencies based on the previous fall soil residual N input is significantly greater than the N efficiencies based on the previous spring fertilizer N input ($p < 0.001$, Tables 3.7, 3.10). Additional tests revealed that the mean N efficiency based on the soil N inventory is significantly greater than immobilization ($p < 0.001$, Table 3.11a). Figures 3.6, 3.10, and 3.13 show this pattern of influence on cover crop N efficiencies. Without standard practices to measure observed N loss and quantify N efficiency, inflated N efficiencies could overestimate anticipated water quality benefits.

5.3.2 Common variables

Three variables frequently appear in empirical and modeling BA and CT experiments: study length, spatial scale, and soil characteristics (Table 3.18). The mean N efficiencies of cover crop studies per method and experiment (n = 33, Tables 3.9a, 3.9b) range from 7-86% and most N efficiencies were influenced by a short-term study length. These studies also observed cover crops on plot-scale cropland areas dominated by well or moderately well drained soils. More than half of the mean N efficiencies are greater than 50%. The N efficiencies greater than 65% are characterized by modeling or empirical methods using primarily CT groundwater N export or soil N experiments. These higher N efficiencies are achieved in less than four years of consecutive cover crop growth and typically include cereal rye crops planted on plot-scale, no-till croplands characterized as hydric soils that are well or moderately well-drained (Table 3.19).

A key finding in my research is that empirical and modeled cover crop N efficiencies increased significantly with data collection years (Fig. 3.5). There are few empirical N efficiencies after 2005 and few modeling studies before 2005; nonetheless, the data collection year is clearly a variable with a large impact on reported cover crop N efficiencies. The available data also show that reported modeling cover crop N efficiencies increased 1.5 times faster than empirical N efficiencies between 1987 and 2018 (Fig. 3.5). There were no significant differences detected between slopes of modeled and empirical cover crop N efficiencies during the growing season; however, modeled mean N efficiencies were significantly greater than empirical by a factor of 1.4 (Fig. 3.9). This assessment of cover crop N efficiencies in the U.S. Coastal Plain

Province shows that modeled cover crop N efficiencies are significantly higher than empirical cover crop N efficiencies, which indicates that progress towards improved water quality in the Chesapeake Bay and other regions will be overestimated by models using the modeled cover crop N efficiencies.

Of the 583 N efficiencies displaying significant levels associated with study length, 77% were based on short-term studies of three years or less (Table 3.15). Studies of 1-3 years showed that consecutive years of cover crop planting increased the N efficiency over time. For example, after two successive years of planting rye cover crops, Ranells et al. (1997) showed that the average N efficiency immobilized by cover crops increased from 6% to 35% during the second year. Staver et al. (1998) demonstrated that rye cover crops planted early and drilled into the soil under ideal conditions could utilize up to 45% of the unharvested N (Tables 3.9a, 3.9b). These short-term studies demonstrate relatively high efficiencies within a few years of successive cover crop planting (Fig. 3.3, Table 3.1), which could introduce bias in the empirical N efficiencies influenced by data collection years shown in Figure 3.5a. Depicting short-term studies at the temporal scale of data collection years can demonstrate preferential experimental methods to measure N, such as via N immobilization, groundwater N export, or soil N inventory, but this can mislead the user who hopes to consistently achieve high cover crop N efficiencies after four or more successive years of cover crop use. Depicting short-term cover crop studies separately from long-term studies using the data collection years time scale could improve our understanding of cover crop N efficiencies over data collection years. However, this research's relatively low number of long-term empirical cover crop studies hindered my ability to draw robust conclusions about improved N efficiencies over data collection years.

In my assessment, soil tillage and hydric soils also influenced N efficiencies. For instance, mean tests showed that empirical cover crop N efficiencies were higher under low and no-tillage practices than empirical conventional till fields (Table 3.8), which were in agreement with Bay Program conservation tillage N efficiencies (Hanson 2018). One notable exception in this assessment found that modeled cover crop N efficiencies based on no-till were significantly greater than empirical N efficiencies, and this indicates that future models incorporating no-till soils should use more conservative cover crop N efficiencies (Table 3.8). Based on the literature reviewed, no detectable differences were found between empirical N efficiencies based on hydric and non-hydric croplands (Table 3.8). However, Yeo et al. (2014), Hively et al. (2020), and Gaimaro et al. (2022) modeled N efficiencies associated with hydric soils and show that N efficiencies are significantly greater than empirical N efficiencies based on hydric soils and non-hydric soils (Table 3.8). Validating these modeled findings, Koskelo et al. (2018) observed that (1) most N export occurred during baseflow, (2) watershed topography, not hydric soils, controlled storm discharge during storm events, and (3) surface ponding on hydric soils intercepted overland flow, reducing the impacts of low infiltration rates. Additional empirical studies applied to hydric and non-hydric soils are needed to substantiate N efficiency differences between non-hydric and hydric croplands.

The cover crop literature emphasizes the need for empirical research at a larger spatial scale to minimize uncertainty in N efficiencies applied to large spatial scales. But empirical watershed scale research is complex due to cooperation from all farmers, coordinating management practices, long-term commitment from researchers, and costs (Mulla et al. 2005; Simpson et al. 2009). In the literature reviewed, modeling scenarios are primarily based on larger watershed scales, whereas empirical studies were applied mainly to croplands <20 ha. The mean

N efficiencies calculated from data produced by the earliest empirical studies that observed cover crops at spatial scales <0.5 ha (termed "field-scale watershed" by Staver et al. 1998, n = 509, 46% ± 1.3) are not significantly different than recent empirical studies (n = 15, 55% ± 6.7) by Aryal et al. (2018) and Fisher et al. (2018), who applied control-treatment groundwater experiments to field-scale croplands (Tables 3.7, 3.13). More empirical field-scaled research is needed to study the long-term effects of cover crops, and empirical results can be used to validate field-scale models. The collective modeling of field- scale cover crop implementation could help improve our understanding of cover crops in a watershed (Table 3.6).

5.3.3 Cover crop efficiency uncertainty

There is a degree of uncertainty in the wide variability in N efficiencies. For example, local empirical studies demonstrate wide-ranging N efficiencies, but tests indicated no significant difference between mean N efficiencies over time ($p = 0.119$, Table 3.6). In contrast, the Phase 6 Chesapeake Bay watershed model uses numerous variants for unique cover crop characteristics, including plant types and planting dates. Each cover crop variant could affect the overall modeled cover crop efficiency (Pickford 2022) and lead to overly optimistic model expectations (NRC 2011; Stephenson et al. 2018). An important finding in my research is that modeling predictions indicate cover crop N efficiencies increase over time and that the modeled mean N efficiencies are significantly greater than empirical cover crop N efficiencies (Fig. 3.5, Table 3.6). This key finding is important because study comparisons give us our first clue about what could influence cover crop N efficiency. Comparisons to empirical research are necessary to validate modeling study outcomes, which are needed to minimize uncertainty in model predictions in the U.S. Coastal Plain, where modeled cover crop N efficiencies predict significant reductions in cover crop efficiency.

5.3.4 Test of hypothesis 2

In my review of 18 empirical and modeling cover crop studies in the Coastal Plain Province, I identified 16 variations of N efficiency formulae used in calculating the 689 N efficiencies ranging from 7 to 86% (Ch. 3, Tables 9a, 9b). The wide-ranging N efficiencies can be attributed to modeling and empirical methods combined with BA and CT experimental methods that evaluated the response of soil N, groundwater N export, and biomass above- and below-ground immobilization with and without cover crop growth over consecutive years of cover crop growth. This research supports the original hypothesis that cover crop BMPs have an adequately tested basis for estimating their N efficiency in the U.S. Coastal Plain province. However, there was significant variation in estimated cover crop efficiencies using different experimental approaches and variables and between empirical and modeling studies.

5.3.5 Agronomic and research recommendations

I recommend that the basis of cover crop N removal capabilities be the N accumulation within the above-ground and below-ground biomass normalized by the fall soil residual N measured after harvest in long-term empirical studies. Additionally, I suggest establishing a standard for reporting cover crop N efficiency. For example, efficiencies based on spring biomass immobilization normalized by the previous spring cash crop fertilizer N input should also report the amount of applied fertilizer removed from cropland by both cash and cover crops.

Reporting cover crop N efficiency and cash crop N use efficiency can offer insight into the spring-applied fertilizer N loss pathways. There is also a need for more field measurements collected over a longer study length to help models incorporate the removal processes of soil and groundwater N in future cover crop models. Models should incorporate cover crop N immobilization, soil N inventories, and groundwater N concentrations to improve our understanding of cover crops' role in reducing N losses from agricultural fields. This cover crop literature review, limited to the United States Coastal Plain province (1980 to 2022), did not find sufficient data on the influence of weather conditions on cover crop N efficiencies; therefore, future research should be conducted to determine the influence of weather conditions and climate change on cover crop N efficiencies, particularly on empirical BA experimental methods, in the United States Coastal Plain province.

However, anthropogenic climate change has likely contributed to increased global average precipitation over land since 1950, with a faster rate of increase since the 1980s (Masson-Delmotte 2021). Moreover, changes in precipitation are expected to increase riverine TN within the continental United States (Renkenberger et al. 2017; Sinha et al. 2017). In a more recent study, Ator et al. (2022) show a slight net decline in annual N export to the Chesapeake Bay between 1995 and 2025 due to increasing rates of denitrification, ammonia volatilization, and changes in plant phenology that offset a wetter climate. However, local field measurements of N export from bay tributaries draining the Delmarva Peninsula show increasing TN and phosphate (Fisher et al. 2021). Schmidt et al. (2019) and Giri et al. (2020) predict a rise in streamflow and surface runoff and increases in agricultural source loads of sediment, nitrogen, and phosphorous under future increases in temperature and precipitation.

Most BMPs continue to reduce nutrient export, but BMP removal efficiencies decline due to more intense runoff events, biological responses to changes in soil moisture and temperature, and intensified upland nutrient losses (Schmidt et al. 2019). A global review of cover crop efficiencies by Thapa et al. (2018) confirms nonleguminous cover crops effectively reduce NO_3^- leaching, improving water quality. Still, cover crop N efficiency is partially influenced by precipitation (Staver et al. 1998; Thapa et al. 2018). Renkenberger et al. (2017) modeling results suggest that in the U.S. Northeast, BMPs designed to remediate water quality problems under the current climate will be insufficient to maintain water quality with climate change. Therefore, existing management practices' designs, including the sizing and materials used, need to adapt, and more widespread BMP applications will be required to meet the impacts of climate change.

5.4 Chapter 4

My third hypothesis was that the three methods of estimating N and P concentrations and yields are in agreement and show a relationship to BMP implementation in the Greensboro watershed. To test this hypothesis, I assessed the influence of progress years (Figs. 4.2 and 4.3), annual discharge (Fig. 4.4), agricultural land-based BMPs (Figs. 4.5 and 4.6), and animal waste management BMPs (Figs. 4.7 and 4.8) on nutrient concentrations and yields derived from three methods: (1) USGS field measurements of concentration and discharge, (2) the WRTDS flow-normalization approach used by the USGS, and (3) CAST modeling. Overall, the USGS methods consistently indicate increasing nutrient concentrations and yields. In contrast, CAST modeling shows decreasing nutrient trends (Table 4.8).

5.4.1 Nutrient inputs: manure, fertilizer, biosolids, direct deposition

Tri-county (Kent County, Delaware, and Caroline and Queen Anne's counties in Maryland) level N inputs significantly increased between 1985 and 2021 ($p < 0.0001$, Fig. 4.9a), which met or exceeded crop N needs (red dash lines) during most progress years. Since 2011, N inputs have exceeded crop N needs and may have increased N concentrations at the USGS gauge. In contrast, tri-county level P inputs decreased even as poultry and livestock manure applications increased since 2000 ($p < 0.0001$, Fig. 4.9b). The P inputs rarely met estimated crop P needs between 1985 and 2021, probably due to rising soil P. This apparent P input imbalance does not explain the recent increases in P export measured at the USGS gauge.

The N contributions from fertilizer and manure range from 57 – 73% and 20 –39% of the annual total N inputs (Fig. 4.10a). Fertilizer contributes the highest source of N annually; however, fertilizer N contributions decreased as manure N increased ($p < 0.0001$). The fertilizer P and manure P contributions vary from 27 – 68% and 23 – 68% of the annual total P inputs (Fig. 4.10b). Figure 10b shows fertilizer P contributions decreased as manure P inputs increased. However, after 2008, livestock and poultry manure has been the dominant source of P. The livestock and poultry manure are likely stored using animal waste management BMPs (Fig. 2.6), revealing that nearly all the applied manure originates from poultry (black dash-dot line).

5.4.2 Manure and fertilizer application rates

Cropland areas receiving N and P inputs from manure (Figs. 4.11a and 4.11d) have not increased as rapidly as the annual application amounts (mass) and rates (per hectare). Consequently, manure N and P application rates have increased significantly from 1985 to 2021 ($p < 0.0001$, Figs. 4.12a and 4.12b). Manure overapplications result in manure nutrient application rates above crop demand (Swaney et al. 2018), and the fertilizer N application rate has increased by 1 kg ha^{-1} y^{-1} (Fig. 4.12a). In contrast, fertilizer P application rates decreased 0.331 kg ha^{-1} y^{-1} as manure P application rates increased by 0.183 kg ha^{-1} y^{-1} and surpassed the application rate of fertilizer P by 2003 (Fig. 4.12b). The largest source of nonpoint P contribution to surface waters is a direct result of manure application (Figs. 4.9 and 4.10). Additionally, the long-term manure application to soils at rates exceeding crop uptake can result in elevated soil-P levels (Staver et al. 1995; Ator et al. 2015), and Staver et al. (1995) found that manure applied to no-till soils increased soluble P in overland flow. Overall, the data shown in Figures 4.11 and 4.12 indicate high amounts of fertilizer N and manure N and P were applied to a disproportionate amount of agricultural croplands. These data support cropland intensification due to increasing N and P applications to croplands due to commercial fertilizer and poultry manure (Fisher et al. 2006a; Fisher et al. 2010; USEPA 2010c; Kleinman et al. 2019).

Despite lowered NUE, farmers apply additional N fertilizer to relatively small areas of croplands in Delmarva to produce higher crop yields of corn (J. Lewis, Uni. of Maryland, pers. com.). The N fertilization rates for corn (starter plus side-dress) are currently around 213 kg N ha^{-1} y^{-1} (190 lbs N ac^{-1} y^{-1}) for dryland farming in Caroline County, Maryland, and increase in the northern counties on the Delmarva Peninsula and for irrigated croplands (J. Lewis, Uni. of Maryland, pers. com.). A partial balance on corn fields in Delmarva is illustrated in Figure 4.15 and shows approximately 50% corn NUE, which is 5% higher than the most recent corn NUE suggested by Swaney et al. (2018). Due to climate change, the growing season has lengthened in Delmarva, and most of the state of Maryland has experienced warmer temperatures and frequent, heavy storm events (USEPA 2016); hence, favorable growing conditions for farmers. The favorable growing conditions contribute to increasing corn fertilization rates and have reportedly yielded more bushels of corn. Thus, farmers expect to increase corn fertilizer rates further to achieve higher corn yields, consistent with the historical trend of increasing fertilizer N rates between 1985 and 2021, shown in Figure 4.12a. Corn NUE should be measured to accurately reflect the corn N uptake in today's climate under higher fertilizer N rates.

5.4.3 N and P watershed inputs and outputs: USGS methods

As manure N and P inputs increased, the export of N and P at the USGS gauge increased only in the measured and WRTDS flow-normalize data (Figs. 4.13, panels a, b, d, and e). Corn crops can use nearly 50% of the N inputs to achieve grain yields, reducing N export. An empirical study by Staver (2001) found that corn could reduce soil nitrate concentrations in the top 30 cm of the root zone to < 1 mg kg^{-1} in croplands that received N applied via fertilizer and poultry manure. Low P export can be partially explained by higher P accumulation rates in soils sampled in dense poultry production areas observed in Delmarva (Sharpley et al. 1994; Noe et al. 2005; Vaughan et al. 2007). Equal slopes tests showed that manure N and P input slopes are significantly greater than the nutrient export slopes shown in panels a, b, d, and e of Figure 4.13 ($p < 0.001$), indicating manure inputs outpace TN and TP exports and potential N and P storage in the watershed. The export also increases over time, resulting from increasing soil P saturation and N mobility via groundwater.

5.4.4 N and P watershed inputs and outputs: CAST-modeling

The CAST-modeled N and P export decreased as manure N and P increased between 1985 and 2021 ($p < 0.0001$, Fig. 4.13, panels c and f). However, USGS measurements (Figs.

4.13, panels a and d) and the WRTDS flow-normalization approach applied by the USGS (Figs. 4.13, panels b and e) reveal increasing nutrient exports as manure N and P inputs increase between 1985 and 2021. Inadequate modeling of factors, such as delivery factors (see below), legacy manure linked to soil-P accumulation and soil-P saturation, and soil tillage practices, partially explains the overestimated nutrient reduction (Figs. 4.13, panels c and f).

Delivery factors

CAST incorporates delivery factors that represent the proportion of nutrient field losses transported via surface waters to the tidal portion of the Chesapeake Bay after accounting for the nutrient and sediment processes that decrease (e.g., denitrification, floodplain deposition) and increase (streambank erosion) nutrient and sediment export (Table 4.9). Much of the calculated TN export from land to surface waters is assumed to be intercepted, and TP reductions occur 100 % of the time, increasing the discrepancy between CAST modeling and USGS calculations.

Legacy manure application: soil-P accumulation and soil-P saturation

The legacy poultry manure applications to croplands have resulted in soil-P accumulation in Delmarva even though Figure 9 in Chapter 4 depicts a mass balance and P inputs rarely meet estimated crop P needs between 1985 and 2021 (Ator et al. 2011; Tiessen et al. 2011; Fertig et al. 2014). Zhang et al. (2023) and Qin et al. (2018) showed that increasing dissolved P transport in the watershed or increasing average P content on suspended sediment is associated with the historical application of poultry manure and continued application of manure based on N content, which results in soil-P above plant needs and subsequent soil-P saturation and export downstream.

Soil tillage

Conservation tillage practices should counter increased dissolved P resulting from no-till practices (Pickford 2022). However, attempts to minimize soil erosion and P loss appear insufficient to counter P concentrations that continue to increase in local streams (Fisher et al. 2006b; Langland et al. 2013). Fanelli et al. (2019) found that manure applications and conservation tillage correlated with increased P concentrations at high flow, suggesting that manure applications increase P concentrations and partially explain the increasing P export at the USGS gauge. Further research is needed to understand the impacts of tillage practices on dissolved and particulate P transport downstream.

5.4.5 Test of hypothesis 3

CAST modeling results support the hypothesis that the historical nutrient data at the Greensboro USGS gauge are related to BMP implementation. However, the USGS methods for estimating nutrient concentrations and yields do not agree with the CAST model outputs and do not support the hypothesis that the three methods are in agreement (Table 4.8).

5.4.6 Agronomic recommendations

The agronomic management practices recommendations are responses to problems caused by anthropogenic land uses. The suggestions below do not address anthropogenic N and P inputs that are likely to continue at current application rates and, in some cases, higher rates. In addition to the recommendations below, I recommend the agricultural community, policy-makers, program managers, and research scientists candidly discuss acceptable water pollution levels given continued nutrient inputs and come to terms with realistic expectations for a healthy waterbody (Beegle 2013; Lucas et al. 2021).

- Develop efficient manure recycling approaches within the local agricultural systems via nutrient management practices and explore decreasing manure applications on cropland where soil P > 100 mg kg^{-1} (Beegle 2013; Lucas et al. 2021)
- Establish a formal manure marketplace for sellers and buyers that can also offset the costs of transporting manure from areas of surplus to deficit areas (Sharpley et al. 2006; Bolan et al. 2010; Spiegal et al. 2020)
- Further research is needed to understand the combined impacts of soil-P saturation and tillage practices.
- Enforce nutrient management plans to ensure practices are followed (Staver 2001).
- Further research and development are needed to explore alternative uses of manure, including composting, methane/energy generation, and granulating/pelletizing (Sharpley et al. 2010; Lim et al. 2023).

5.4.7 Modeling recommendations

Modeling and empirical measurements are needed to disentangle multi-layered and often interrelated factors contributing to eutrophication in complex ecosystems, such as the Chesapeake Bay, Baltic Sea, Gulf of Mexico, and other basins. However, program managers must choose the appropriate model given the modeling capabilities, such as assessing multiple environmental variables (Xie et al. 2015). Program managers must also understand the limitations of modeling results (Liu et al. 2017b) and subsequent applications policy development, estimating BMP effectiveness, or targeting locations for BMPs (Sith et al. 2019; Amin et al. 2020; Stephenson et al. 2021). Below, I offer recommendations to improve modeling efforts.

- Improve CAST output with more validation from USGS observations.
- WRTDS flow normalization is based on the concept that there are large and random interannual variations around an unchanging mean discharge. Investigate whether the interannual increases in mean discharge observed at Greensboro invalidate the use of flow normalization (Fig. 4.1).
- Adjust N and P efficiencies to reflect the lifespan of cultural and structural BMPs.
- Incorporate nutrient transport via artificial drainage ditches that bypass natural flow pathways and exacerbate N and P transport (Sharpley et al. 2006; Kleinman et al. 2007; Needelman et al. 2007).
- Factor soil-P accumulation and subsequent soil-P saturation due to annual manure applications, resulting in particulate and dissolved P export via groundwater and overland flows (Sharpley et al. 1994).
- Improve modeled P output due to increased import of animal feed (Sharpley et al. 1994; Sharpley et al. 2006; Bolan et al. 2010).

5.5 Influential factors

This dissertation revealed that modeling studies overestimate cover crop N efficiencies in the Coastal Plain Province and that CAST modeling is not in agreement with the USGS field measurements. CAST-modeled nutrient concentrations and yields decrease over time, indicating improvements in water quality. In contrast, USGS methods consistently show that nutrient concentrations and yields increase, indicating that BMPs are insufficient, malfunctioning, overwhelmed by nutrient inputs, or efficiencies are overestimated. The BMP implementation data shows that farmers increased their use of animal waste management systems in parallel with no significant changes in manure transport. In turn, more manure N and P applications onto croplands likely resulted in soil accumulation and subsequent saturation, increasing N and P losses via groundwater and overland flows reflected in increasing N and P measurements at the USGS gauging station. In the following sections, I discuss the main influential factors that may have affected modeled and empirical cover crop N efficiencies, nutrient inputs linked to global animal protein demand and agricultural intensity, and uncertainty due to climate change.

5.5.1 Modeled versus empirical cover crop N efficiencies

A review of agricultural BMP effectiveness models conducted by Xie et al. (2015) indicates that modeling methods are spatially and temporally scale-dependent. The bay-level model uses coarse spatial data to determine load reduction goals, but Amin et al. (2020) suggest that finer-scale spatial data should replace coarse spatial resolution if regulatory plans are developed. Spatial data of higher resolution cannot consider the heterogeneity in local conditions, which affects BMP effectiveness (Amin et al. 2020). In the modeling studies assessed for my research, models utilize remotely sensed Landsat satellite imagery with a spatial resolution of 30 meters in watersheds no larger than 300 km^2. Considering the watershed area and imagery spatial resolution, there is potential for bias in the N efficiency because the spatial data may be too coarse to provide accurate cover crop N efficiencies that apply to smaller spatial scales (Dark et al. 2016). This means the basis of regulatory plans, such as the TMDL, should be finer-scale spatial data instead of coarse data.

Additionally, Liu et al. (2017b) indicate most BMP efficiency models assume constant nutrient removal performance based on expected maintenance and performance over the life of the BMP. However, (Hively et al. 2020) modeled 10 years of consecutive cover crop applications, and the results indicate N efficiency increased in subsequent years rather than remaining constant. The improved modeled performance suggests the modeled properties of the cover crops improved over time or the modeled environmental conditions supplied more N for plant uptake (Fig. 7a). However, as BMPs age, their nutrient removal capacity will likely change irrespective of maintenance because structures wear down and, in some cases, pollutants accumulate (Liu et al. 2017b). Although long-term empirical cover crop studies are limited, the results by Staver et al. (1998) demonstrated N efficiencies gradually declined each year after nine consecutive years of cover crop growth due to the depletion of soil N inventories and groundwater N concentrations (Fig. 3.7c). Liu et al. (2017b) also found that the water quality impacts of BMPs implemented at the watershed scale have not been as rapid or large as expected, possibly due to overly high expectations for the BMPs' long-term efficiency.

5.5.2 Intensive agriculture

A shrinking global agricultural workforce and less cropland are a few reasons for the emergence of agricultural intensification, where farmers aim to produce higher crop yields and animal-based products from less land area. In 2000, 40% of the global workforce was employed in agriculture. By 2020, 27% of the worldwide workforce, or 874 million persons, were employed in agriculture (FAO 2021b). Moreover, one-third of the global land area in 2019 was agricultural land, but less than 35% of the agricultural land was cropland. The remaining agricultural land uses comprised permanent meadows and pastures (FAO 2021a).

A growing world human population demanding higher proportions of animal protein in their diet required intensive agricultural land use practices to meet global demands (Tilman et al. 2002; Foley et al. 2005; Lassaletta et al. 2013; Ruiz-Martinez et al. 2015). For example, between 1985 and 2010, as the human population grew by 38%, animal protein production grew by 60% (Lassaletta et al. 2013). During this same period, the production of animal goods increased by 300%, in China, partly because animal protein in the human diet increased from 19% to 30%, despite the human population in China only growing by 24%. From 1961 to 2007, animal protein consumption in the typical Mediterranean diet increased by 34% to levels where the majority (64%) of the Mediterranean diet is animal protein. To maintain this Western diet, the amount of N net imported to Spain, primarily as animal feed, equaled the total national crop production (Lassaletta et al. 2013).

The number of livestock per confined animal feeding operation increased for all major livestock types. Chicken, pig, and cattle accounted for nearly 90% of the global production between 2000 and 2018. By 2019, the world's meat production reached 337 million tons, up 44%, or 103 million tons, compared with 2000 (FAO 2021b). However, a significant shift from dairy cattle (decreased 14%) to poultry and swine populations (increased by 91% and 48%, respectively) marked the animal protein preference in diets (Kellogg et al. 2014). The United States makes 18% of the world's chicken and cattle meat, and a significant share of American meat production (especially chicken) is exported (FAO 2021b). In contrast, China produces 40% of the world's pig meat primarily for domestic consumption. The world population reached 8 billion on 15 November 2022 and is expected to increase by nearly 2 billion persons in the next

30 years (per the United Nations). Therefore, the consumption of animal-based goods is likely to rise in the future in developing and developed countries (Lassaletta et al. 2013).

Intensive, large-scale, confined animal operations have become more spatially concentrated in high-production areas. These confined animal feeding operations include poultry agriculture in Delmarva located in the largest estuary basin in the United States, Chesapeake Bay (Mozaffari et al. 1994; Simon et al. 2005; Nino de Guzman et al. 2012; Fertig et al. 2014), and Arkansas (Rodriguez et al. 2011), the swine and poultry agriculture in the Pamlico Sound/Neuse River watershed in North Carolina, the second largest lagoonal estuary in the United States (Rothenberger et al. 2009; Brown et al. 2020), the poultry industry in China (Wang et al. 2018) and dairy farming systems in the US (e.g., southeastern New York), northern Italy, and New Zealand (James et al. 2007; Yang et al. 2017; Bechini et al. 2020). As livestock production has become more spatially concentrated and widespread, manure nutrients have grown much faster relative to the assimilative capacity of land available for manure spreading, which often exceeds the individual farm's capacity. Consequently, the limits of animal waste recycling have led to widespread manure surpluses, unused manure N and P in the ecosystem, and subsequent water quality issues (Kellogg et al. 2014).

Intensive agriculture has contributed a disproportionate amount of N and P to fresh, estuarine, and coastal waters worldwide (Foley et al. 2005; Howden et al. 2013; Svanback et al. 2019; Zou et al. 2020). For example, in the Baltic Sea catchment, large N and P surpluses often occurred in regions with high livestock density, and imports of mineral fertilizers and feed to the catchment increased overall N and P surpluses, increasing the risk of nutrient losses from agriculture to the aquatic environment (Svanback et al. 2019). In the Loire River basin in France, intensive farming practices during the 20th century were linked to eutrophication that started during the 1960–1970 period and persists today (Foucher et al. 2020). The long-term mean monthly nitrate concentrations in the River Thames catchment, the second largest in the United Kingdom, show an overall increase after the 1970s largely due to postwar fertilizer inputs and growing livestock populations (Howden et al. 2013). Additionally, in the largest estuary in the United States, agriculture is the largest single source of N, P, and total suspended sediment (TSS) to the Chesapeake Bay (Boesch 2001; Kemp et al. 2005; Ator et al. 2020). Agricultural nonpoint sources contributed approximately 44% of the N and P to the Chesapeake Bay watershed due to added fertilizer, animal manure, and tilling croplands (USEPA 2010c).

5.5.3 Climate change

Global average temperatures have risen since the 1950s (Lobell et al. 2011), and increasing air temperatures and changes in precipitation patterns and intensity are anticipated throughout the U.S. over the 21st century (Melillo et al. 2014). Anthropogenic climate change has likely contributed to increased global average precipitation over land since 1950, with a faster rate of increase since the 1980s (Masson-Delmotte 2021). Additionally, applications of simple linear regression by Rice et al. (2017) project watersheds north of the Pennsylvania-Maryland state border will have higher annual mean discharge in 2025, the target date for implementing the Chesapeake Bay TMDL, and this is in agreement with the annual average discharge increases measured at the USGS gauging station in Greensboro watershed (Fig. 3.1).

These changes in precipitation are expected to increase riverine TN within the continental United States (Renkenberger et al. 2017; Sinha et al. 2017). Moreover, Schmidt et al. (2019) and Giri et al. (2020) predict a rise in streamflow and surface runoff and increases in agricultural source loads of sediment, nitrogen, and phosphorous under future increases in temperature and precipitation. However, in a recent study, Ator et al. (2022) show a slight net decline in annual N export to the Chesapeake Bay between 1995 and 2025 due to increasing rates of denitrification, ammonia volatilization, and changes in plant phenology that offset a wetter climate. Conversely, empirical field measurements of N export from the bay tributaries draining the Delmarva Peninsula show increasing TN and phosphate (Fisher et al. 2021). Moreover, a recent modeling study by Bhatt et al. (2023) shows climate change will increase streamflow (2.3%– 6.2%), sediment (3.8%– 18.8%), N (2.6%– 10.8%), and P (4.5%– 26.7%) loads to the Chesapeake Bay.

There is a growing scientific consensus on climate change and its impact on agricultural mitigation efforts to abate anthropogenic eutrophication because the N and P reduction goals needed to achieve water quality and the BMP efficiencies measurement of pollutant removal performance are generally based on historical climate (Schmidt et al. 2019). For example, Schmidt et al. (2019) model prediction shows BMPs in the United States Midwest and Coastal Plain continue to reduce nutrient export, but BMP removal efficiencies decline due to more intense runoff events, biological responses to changes in soil moisture and temperature, and intensified upland nutrient losses. Moreover, Renkenberger et al. (2017) modeling results suggest that in the U.S. Northeast, BMPs designed to remediate water quality problems under the current climate will be insufficient to maintain water quality with climate change. The model predictions by Giri et al. (2020) support Renkenberger et al. (2017) findings. In turn, Giri et al. (2020) suggest that the nutrient removal capabilities of cover crops, filter strips, and no-till could negate the climate change impact on water fluxes and water quality in Southern New Jersey with more widespread implementation. BMP adaptations to climate change will require more applications that are much more widespread within watersheds, and in some cases, program managers will need to redesign existing BMPs to adapt to climate change impacts.

Appendices

A Best management practice (BMP) variants

Table A1. Classification of agricultural sector BMP variants. Abbreviations: "Type" represents a Cultural (C), Structural (S), or structural with annual maintenance (SM.) BMP. "Unit Type" denotes application to an area (km^2, hectares, or m^2), the area treated (km^2, hectares, or m^2), or Count.

Agricultural BMP variant	BMP Classification	Type	Unit Type
Alternative Crops	Alternative Crops	C	Area
Barnyard Runoff Control	Barnyard Runoff Control	SM.	Area
Cover Crop Commodity Early	Commodity cover crop	C	Area
Cover Crop Commodity Late	Commodity cover crop	C	Area
Cover Crop Commodity Normal	Commodity cover crop	C	Area
Soil Conservation and Water Quality Plans	Conservation Plan	C	Area
Cover Crop Traditional Annual Legume Early Aerial	Cover crop	C	Area
Cover Crop Traditional Annual Legume Early Other	Cover crop	C	Area
Cover Crop Traditional Annual Legume Normal Other	Cover crop	C	Area
Cover Crop Traditional Annual Ryegrass Early Aerial	Cover crop	C	Area
Cover Crop Traditional Annual Ryegrass Early Drilled	Cover crop	C	Area
Cover Crop Traditional Annual Ryegrass Normal Other	Cover crop	C	Area
Cover Crop Traditional Barley Early Aerial	Cover crop	C	Area
Cover Crop Traditional Barley Early Drilled	Cover crop	C	Area
Cover Crop Traditional Barley Early Other	Cover crop	C	Area
Cover Crop Traditional Barley Normal Drilled	Cover crop	C	Area
Cover Crop Traditional Barley Normal Other	Cover crop	C	Area
Cover Crop Traditional Brassica Early Aerial	Cover crop	C	Area
Cover Crop Traditional Brassica Early Drilled	Cover crop	C	Area
Cover Crop Traditional Brassica Early Other	Cover crop	C	Area
Cover Crop Traditional Forage Radish Early Aerial	Cover crop	C	Area
Cover Crop Traditional Forage Radish Early Drilled	Cover crop	C	Area
Cover Crop Traditional Forage Radish Early Other	Cover crop	C	Area
Cover Crop Traditional Forage Radish Plus Early Drilled	Cover crop	C	Area
Cover Crop Traditional Forage Radish Plus Normal Drilled	Cover crop	C	Area
Cover Crop Traditional Forage Radish Plus Normal Other	Cover crop	C	Area
Cover Crop Traditional Legume Plus Grass 25-50% Early Aerial	Cover crop	C	Area
Cover Crop Traditional Legume Plus Grass 25-50% Early Drilled	Cover crop	C	Area
Cover Crop Traditional Legume Plus Grass 25-50% Normal Drilled	Cover crop	C	Area
Cover Crop Traditional Legume Plus Grass 25-50% Normal Other	Cover crop	C	Area
Cover Crop Traditional Legume Plus Grass 50% Early Aerial	Cover crop	C	Area
Cover Crop Traditional Legume Plus Grass 50% Early Drilled	Cover crop	C	Area
Cover Crop Traditional Legume Plus Grass 50% Normal Drilled	Cover crop	C	Area

Agricultural BMP variant	BMP Classification	Type	Unit Type
Cover Crop Traditional Legume Plus Grass 50% Normal Other	Cover crop	C	Area
Cover Crop Traditional Oats, Winter Hardy Early Aerial	Cover crop	C	Area
Cover Crop Traditional Oats, Winter Hardy Early Drilled	Cover crop	C	Area
Cover Crop Traditional Oats, Winter Hardy Normal Drilled	Cover crop	C	Area
Cover Crop Traditional Oats, Winter Killed Early Other	Cover crop	C	Area
Cover Crop Traditional Rye Early Aerial	Cover crop	C	Area
Cover Crop Traditional Rye Early Drilled	Cover crop	C	Area
Cover Crop Traditional Rye Early Other	Cover crop	C	Area
Cover Crop Traditional Rye Late Drilled	Cover crop	C	Area
Cover Crop Traditional Rye Late Other	Cover crop	C	Area
Cover Crop Traditional Rye Normal Drilled	Cover crop	C	Area
Cover Crop Traditional Rye Normal Other	Cover crop	C	Area
Cover Crop Traditional Triticale Early Aerial	Cover crop	C	Area
Cover Crop Traditional Triticale Early Drilled	Cover crop	C	Area
Cover Crop Traditional Triticale Early Other	Cover crop	C	Area
Cover Crop Traditional Triticale Late Drilled	Cover crop	C	Area
Cover Crop Traditional Triticale Late Other	Cover crop	C	Area
Cover Crop Traditional Triticale Normal Drilled	Cover crop	C	Area
Cover Crop Traditional Triticale Normal Other	Cover crop	C	Area
Cover Crop Traditional Wheat Early Aerial	Cover crop	C	Area
Cover Crop Traditional Wheat Early Drilled	Cover crop	C	Area
Cover Crop Traditional Wheat Early Other	Cover crop	C	Area
Cover Crop Traditional Wheat Late Drilled	Cover crop	C	Area
Cover Crop Traditional Wheat Late Other	Cover crop	C	Area
Cover Crop Traditional Wheat Normal Drilled	Cover crop	C	Area
Cover Crop Traditional Wheat Normal Other	Cover crop	S	Area
Forest Buffer	Forest Buffer	S	Area
Forest Buffer Nitrogen Upland Acres	Forest Buffer	S	Area
Forest Buffer Phosphorus and Sediment Upland Acres	Forest Buffer	S	Area
Forest Buffer-Narrow with Exclusion Fencing	Forest Buffer w/ exclusion fencing	S	Area
Forest Buffer-Streamside with Exclusion Fencing	Forest Buffer w/ exclusion fencing	S	Area
Forest Buffer-Streamside with Exclusion Fencing Nitrogen Upland Acres	Forest Buffer w/ exclusion fencing	S	Area
Forest Buffer-Streamside with Exclusion Fencing Phosphorus and Sediment Upland Acres	Forest Buffer w/ exclusion fencing	S	Area
Grass Buffer	Grass Buffer	S	Area
Grass Buffer Nitrogen Upland Acres	Grass Buffer	S	Area
Grass Buffer Phosphorus and Sediment Upland Acres	Grass Buffer	S	Area
Grass Buffer-Narrow with Exclusion Fencing	Grass Buffer	S	Area
Grass Buffer-Streamside with Exclusion Fencing	Grass Buffer w/ exclusion fencing	S	Area
Grass Buffer-Streamside with Exclusion Fencing Nitrogen Upland Acres	Grass Buffer w/ exclusion fencing	S	Area

Agricultural BMP variant	BMP Classification	Type	Unit Type
Grass Buffer-Streamside with Exclusion Fencing Phosphorus and Sediment Upland Acres	Grass Buffer w/ exclusion fencing	C	Area
Horse Pasture Management	Horse Pasture Management	S	Area
Land Retirement to Ag Open Space	Land retirement	S	Area
Land Retirement to Pasture	Land retirement	S	Area
Loafing Lot Management	Loafing Lot Management	C	Area
Manure Incorporation Low Disturbance Late	Manure incorporation or injection	C	Area
Manure Injection	Manure incorporation or injection	C	Area
Nutrient Management Core N	Nutrient Management N	C	Area
Nutrient Management N Placement	Nutrient Management N	C	Area
Nutrient Management N Rate	Nutrient Management N	C	Area
Nutrient Management N Timing	Nutrient Management N	C	Area
Nutrient Management Core P	Nutrient Management P	C	Area
Nutrient Management P Placement	Nutrient Management P	C	Area
Nutrient Management P Rate	Nutrient Management P	S	Area
Off Stream Watering Without Fencing	Off Stream Watering w/o Fencing	C	Area
Precision Intensive Rotational/Prescribed Grazing	Pasture and grazing management practices	C	Area
Tillage Management - Conservation	Tillage - Conservation	C	Area
Tillage Management - Continuous High Residue	Tillage - High residue	C	Area
Tillage Management - Low Residue	Tillage - Low residue	C	Area
Tree Planting	Tree Planting	S	Area
Water Control Structures	Water Control Structures	S	Area
Wetland Creation Upland Acres	Wetland Creation	S	Area
Wetland Rehabilitation Upland Acres	Wetland Restoration or Rehabilitation	SM	Area
Wetland Restoration Upland Acres	Wetland Restoration or Rehabilitation	SM	Area

Table A2. Classification of developed sector BMP variants. Abbreviations: "Type" represents a Cultural (C), Structural (S), or structural with annual maintenance (SM.) BMP. "Unit Type" denotes application to an area (km^2, hectares, or m^2), the area treated (km^2, hectares, or m^2), or Count.

Development BMP variant	BMP Classification	Type	Unit Type
Dry Detention Ponds and Hydrodynamic Structures	Dry detention ponds	SM	Area
Dry Extended Detention Ponds	Dry detention ponds	SM	Area
Erosion and Sediment Control Level 1	Erosion and sediment control	S	Area
Erosion and Sediment Control Level 2	Erosion and sediment control	S	Area
Filtering Practices	Filtering Practices	S	Area treated
Urban Forest Buffer Upland Acres	Forest Buffer	S	
Infiltration Practices w/ Sand, Veg. - A/B soils, no underdrain	Infiltration practices	S	Area treated
Infiltration Practices w/o Sand, Veg. - A/B soils, no underdrain	Infiltration practices	S	Area treated
Permeable Pavement w/o Sand, Veg. - A/B soils, no underdrain	Infiltration practices	S	Area treated
Vegetated Open Channels - A/B soils, no underdrain	Infiltration practices	S	Area treated
Nutrient Management Maryland Commercial Applicators	Nutrient Management Dev. Plan	S	Area
Nutrient Management Maryland Do It Yourself	Nutrient Management Dev. Plan	S	Area
Nutrient Management Plan	Nutrient Management Dev. Plan	S	Area
Nutrient Management Plan High Risk Lawn	Nutrient Management Dev. Plan	S	Area
Bioretention/raingardens - A/B soils, underdrain	Stormwater Performance Standards	SM	Area treated
Bioretention/raingardens - C/D soils, underdrain	Stormwater Performance Standards	SM	Area treated
Bioswale	Stormwater Performance Standards	SM	Area treated
Stormwater Performance Standard-Runoff Reduction	Stormwater Performance Standards	S	Area treated
Stormwater Performance Standard-Stormwater Treatment	Stormwater Performance Standards	S	Area treated
Advanced Sweeping Technology - 1 pass/12 weeks	Street sweeping	S	Area
Forest Planting	Tree planting	S	Area
Tree Planting - Canopy	Tree Planting	S	Area
Wet Ponds and Wetlands	Wet Ponds and Wetlands	S	Area

Table A3. Classification of natural sector BMP variants. Abbreviations: “Type” represents a Cultural (C), Structural (S), or structural with annual maintenance (SM) BMP. “Unit Type” denotes application to an area (km^2, hectares, or m^2), the area treated (km^2, hectares, or m^2), the length (m, km) or Count.

Natural BMP variant	BMP Classification	Type	Unit type
Forest Harvesting Practices	Forest Harvesting Practices	S	Area
Non Urban Stream Restoration	Non-Urban Stream Restoration	S	Length
Wetland Rehabilitation	Wetland Rehabilitation	SM	Area

Table A4. Classification of septic sector BMP variants. Abbreviations: “Type” represents a Cultural (C), Structural (S), or structural with annual maintenance (SM.) BMP. “Unit Type” denotes application to an area (km^2, hectares, or m^2), the area treated (km^2, hectares, or m^2), or Count.

Septic BMP variant	BMP Classification	Type	Unit type
Septic Connection	Septic Connection	S	Count
Septic Denitrification - Conventional	Septic Denitrification - Conventional	S	Count
Septic Effluent - Advanced	Septic Effluent - Advanced	S	Count
Septic Effluent - Enhanced	Septic Effluent - Enhanced	S	Count
Septic Pumping	Septic Pumping	C	Count

Table A5. Classification of animal sector BMP variants. Abbreviations: “Type” represents a Cultural (C), Structural (S), or structural with annual maintenance (SM) BMP. “Unit Type” denotes application to an area (km^2, hectares, or m^2), the area treated (km^2, hectares, or m^2), or Count.

Animal BMP variant	BMP Classification	Type	Unit type
Animal Waste Management System	Animal Waste Management System	S	AU
Mortality Composters	Mortality Composters	S	AU
Poultry Litter Amendments (e.g. alum)	Poultry Litter Amendments (e.g., alum)	C	AU
Riparian Fence	Riparian Fence	S	AU

Table A6. Classification of manure transport sector BMP variants. Abbreviations: “Type” represents a Cultural (C), Structural (S), or structural with annual maintenance (SM.) BMP. “Unit Type” denotes application to an area (km^2, hectares, or m^2), the area treated (km^2, hectares, or m^2), or Count. Manure transport is based on a county scale.

Animal BMP variant	**BMP Classification**	**Type**	**Unit type (dry weight)**
Manure transport	Manure transport	C	Dry or metric tons

Table A7. Manure from Caroline, Queen Anne’s, and Kent counties are transported to counties in four neighboring states. Bold county names indicate a jurisdiction containing part of the Greensboro watershed.

	Manure recipient (County)			
	Maryland	Delaware	Virginia	Pennsylvania
Manure from Caroline County, Maryland				
	Cecil	Kent	Westmoreland	
	Dorchester			
	Kent			
	Queen Anne’s			
	St. Mary’s			
	Talbot			
	Washington			
Manure from Queen Anne’s County, Maryland				
	Anne Arundel			
	Caroline			
	Kent			
	Washington			
Manure from Kent County, Delaware				
	Anne Arundel	New Castle	Accomack	Chester
	Calvert	Sussex	Caroline	
	Caroline		Essex	
	Cecil		Lancaster	
	Charles		Northumberland	
	Dorchester		Westmoreland	
	Frederick			
	Kent			
	Queen Anne’s			
	Somerset			
	St. Mary’s			
	Talbot			
	Wicomico			

B Total area of best management practices (BMPs) by load sources, 2010 vs 2021

Table B. The load source BMP area (ha) is the sum of three land river segments forming the Greensboro watershed. Abbreviation: "Load source" represents the load source within a sector, "Nutrient allocation" is the designated load allocation where "LA" references loads from land areas and "WLA" represents loads from waste, the BMP area (ha) is the land area in 2010 and 2021 progress years affected by BMPs, and "2021 Pre-BMP area (ha) is the area before load source conversion BMPs are applied. Source: CAST base conditions report.

Load Source	Nutrient allocation	2010 BMP area (ha)	2021 Pre-BMP area (ha)	2021 BMP area (ha)
Agriculture loading sources (ha)				
Ag Open Space	LA	10	9	83
Double Cropped Land	LA	2,598	928	907
Full Season Soybeans	LA	1,872	3,666	3,643
Grain with Manure	LA	2,311	2,629	2,596
Grain without Manure	LA	1,456	1,207	1,198
Leguminous Hay	LA	184	118	116
Non-Permitted Feeding Space	LA	11	7	7
Other Agronomic Crops	LA	646	747	736
Other Hay	LA	409	384	379
Pasture	LA	673	507	513
Permitted Feeding Space	WLA	6	16	16
Silage with Manure	LA	62	22	22
Silage without Manure	LA	11	4	4
Small Grains and Grains	LA	405	1,160	1,150
Specialty Crop High	LA	284	191	190
Specialty Crop Low	LA	436	220	219
Total Agriculture (ha)		11,374	11,815	11,779
Rural-urban development loading sources (ha)				
MS4 Buildings and Other	WLA	0	0	0
MS4 Roads	WLA	0	0	0
MS4 Tree Canopy over Impervious	WLA	0	0	0
MS4 Tree Canopy over Turf Grass	WLA	0	0	0
MS4 Turf Grass	WLA	2	3	3
Non-Regulated Buildings and Other	LA	424	448	448
Non-Regulated Roads	LA	301	321	321
Non-Regulated Tree Canopy over Impervious	LA	97	98	98
Non-Regulated Tree Canopy over Turf Grass	LA	183	196	196
Non-Regulated Turf Grass	LA	2,506	2,466	2,466
Regulated Construction	WLA	13	3	3
Total Developed (ha)		3,526	3,535	3,535
Natural load sources (ha)				
Harvested Forest	LA	79	74	74
Headwater or Isolated Wetland	LA	8,122	7,907	7,907
Mixed Open	LA	1,123	948	948
Non-tidal Floodplain Wetland	LA	810	789	809
True Forest	LA	4,966	4,938	4,954
Water	LA	326	323	323
Total Natural (ha)		15,426	14,979	15,015
Total stream bed and bank (km)	LA	265	0	265
Total number of septic systems	LA	3,362	0	3,443

C Average edge-of-stream loading rate comparisons: 2021 vs no BMP

Table C. The average edge-of-stream (EOS) loading rate is comprised of loading rates, each representing one of three land river segments forming the Greensboro watershed. The No BMP average loading rate is based on the 2010 No action CAST scenario. The BMP average loading rate is based on the 2021 BMP implementation scenario. Load Source lists the various load sources per sector, "No BMP" is the nutrient loading rate where no BMPs are implemented, "2021 BMP" is the nutrient loading rate where BMPs are implemented in 2021, "LR diff" represents the change in nutrient loading rate. Source: CAST loads per unit report.

	Nitrogen average loading rate (kg ha^{-1})			**Phosphorus average loading rate (kg ha^{-1})**			**Total suspended solids (Sediment) average loading rate (kg ha^{-1})**		
Load Source	**No BMP**	**2021 BMP**	**LR diff**	**No BMP**	**2021 BMP**	**LR diff**	**No BMP**	**2021 BMP**	**LR diff**
<u>Agriculture sector loading sources</u>									
Ag Open Space	5.16	4.87	-0.29	0.78	0.62	-0.16	8.96	9.75	0.79
Double Cropped Land	38.31	28.82	-9.49	0.90	0.56	-0.34	450.20	180.70	-269.50
Full Season Soybeans	30.44	24.33	-6.11	0.73	0.49	-0.25	486.30	184.41	-301.89
Grain with Manure	62.98	47.29	-15.69	0.80	0.50	-0.30	398.73	152.60	-246.13
Grain without Manure	40.73	29.90	-10.83	0.79	0.54	-0.25	400.43	154.96	-245.47
Leguminous Hay	9.66	9.00	-0.66	0.23	0.20	-0.03	31.69	28.50	-3.20
Non-Permitted Feeding Space	1426.93	310.27	-1116.66	56.81	11.21	-45.60	562.72	420.16	-142.56
Other Agronomic Crops	20.60	15.27	-5.33	1.15	0.77	-0.38	150.38	59.80	-90.58
Other Hay	14.93	15.17	0.24	0.59	1.03	0.44	9.46	8.51	-0.95
Pasture	15.62	16.20	0.58	1.41	1.72	0.31	17.52	15.14	-2.38
Permitted Feeding Space	1754.81	270.82	-1483.99	76.52	11.46	-65.06	562.72	420.16	-142.56
Silage with Manure	51.46	46.29	-5.17	0.91	0.58	-0.32	731.41	287.04	-444.37
Silage without Manure	19.51	37.22	17.71	0.87	0.60	-0.27	731.41	287.04	-444.37
Small Grains and Grains	35.81	24.76	-11.05	0.81	0.49	-0.32	563.81	215.66	-348.15
Specialty Crop High	54.90	44.55	-10.35	2.20	1.77	-0.43	789.19	692.04	-97.15
Specialty Crop Low	14.08	13.17	-0.91	2.04	1.90	-0.14	745.91	626.54	-119.37

Table C. (continued) The average edge-of-stream (EOS) loading rate.

Load Source	Nitrogen average loading rate (kg ha^{-1}) No BMP	2021 BMP	LR diff	Phosphorus average loading rate (kg ha^{-1}) No BMP	2021 BMP	LR diff	Total suspended solids (Sediment) average loading rate (kg ha^{-1}) No BMP	2021 BMP	LR diff
Rural-urban development sector loading sources									
MS4 Buildings and Other	18.70	18.57	-0.14	0.65	0.64	-0.01	317.44	312.27	-5.17
MS4 Roads	23.53	23.51	-0.02	0.80	0.80	0.00	354.37	353.86	-0.51
MS4 Tree Canopy over Impervious	21.29	21.14	-0.16	0.70	0.69	-0.01	317.43	312.32	-5.12
MS4 Tree Canopy over Turf Grass	9.77	9.47	-0.30	0.70	0.65	-0.04	63.49	62.42	-1.07
MS4 Turf Grass	12.83	12.43	-0.40	0.91	0.86	-0.05	108.34	106.63	-1.72
Non-Regulated Buildings and Other	18.65	18.55	-0.10	0.66	0.66	-0.01	317.21	313.56	-3.64
Non-Regulated Roads	23.57	23.44	-0.13	0.80	0.79	-0.01	317.21	313.56	-3.65
Non-Regulated Tree Canopy over Impervious	21.49	21.38	-0.12	0.72	0.71	-0.01	181.90	179.70	-2.20
Non-Regulated Tree Canopy over Turf Grass	9.77	9.38	-0.39	0.80	0.76	-0.04	62.51	61.76	-0.75
Non-Regulated Turf Grass	12.82	12.31	-0.51	1.05	1.00	-0.05	108.64	107.43	-1.21
Regulated Construction	29.84	29.84	0.00	3.01	3.01	0.00	1496.57	294.88	-1201.69
Natural sector loading sources									
Harvested Forest	16.61	10.39	-6.22	0.19	0.10	-0.09	29.63	16.71	-12.92
Headwater or Isolated Wetland	1.83	1.83	0.00	0.05	0.05	0.00	2.05	2.05	0.00
Mixed Open	2.64	2.64	0.00	0.22	0.22	0.00	162.23	162.23	0.00
Non-tidal Floodplain Wetland	1.83	1.83	0.00	0.05	0.05	0.00	2.05	2.05	0.00
Stream Bed and Bank		401.78			76.19			232,195.30	
True Forest	1.83	1.83	0.00	0.05	0.05	0.00	2.04	2.04	0.00
Water	10.55	10.55	0.00	0.67	0.67	0.00	0.00	0.00	0.00

D BMP variants applied to load sources in the Greensboro watershed

Table D1. The number of agricultural load sources affected by BMP variants is provided in the table. The "x" denotes the application of an agricultural BMP variant onto an agricultural load source in the Greensboro watershed. This level of detail means the reduction capacity of a BMP could vary depending on the load source. Abbreviations: "**DC**" = Double Cropped Land, "**Soy**" = Full Season Soybeans, "**OAg**" = Other Agronomic Crops, "**SmGG**" = Small Grains and Grains, "**GM**" = Grain with Manure, "**Gr**" = Grain without Manure, "**SM**" = Silage with Manure, "**Sil**" = Silage without Manure, "**Ttl DLS**" = total develop load source categories affected by Development BMP variants, "Units" indicate the common measurement of development BMP variants.

	Greensboro watershed Agriculture Load Source (ALS)									
Reclassified agricultural BMP variants	**"DC"**	**"Soy"**	**"OAg"**	**"SmGG"**	**"GM"**	**"Gr"**	**"SM"**	**"Sil"**	**Total ALS affected by BMP**	**Unit**
Alternative Crops	x	x	x	x	x	x	x	x	8	area
Barnyard Runoff Control									0	area
Cover Crop Commodity Normal	x			x					2	area
Cover Crop Traditional	x	x	x	x	x	x	x	x	8	area
Forest Buffer	x	x	x	x	x	x	x	x	8	area
Forest Buffer Nitrogen Upland	x	x	x	x	x	x	x	x	8	area
Forest Buffer Phosphorus and Sediment Upland	x	x	x	x	x	x	x	x	8	area
Forest Buffer-Narrow with Exclusion Fencing									0	area
Forest Buffer-Streamside with Exclusion Fencing									0	area
Forest Buffer-Streamside with Exclusion Fencing Nitrogen Upland									0	area
Forest Buffer-Streamside with Exclusion Fencing Phosphorus and Sediment Upland									0	area
Grass Buffer	x	x	x	x	x	x	x	x	8	area
Grass Buffer Nitrogen Upland	x	x	x	x	x	x	x	x	8	area
Grass Buffer Phosphorus and Sediment Upland	x	x	x	x	x	x	x	x	8	area
Grass Buffer-Narrow with Exclusion Fencing									0	area
Grass Buffer-Streamside with Exclusion Fencing									0	area
Grass Buffer-Streamside with Exclusion Fencing Nitrogen Upland									0	area
Grass Buffer-Streamside with Exclusion Fencing Phosphorus and Sediment Upland									0	area
Horse Pasture Management									0	area
Land Retirement to Ag Open Space	x	x	x	x	x	x	x	x	8	area
Land Retirement to Pasture	x	x	x	x	x	x	x	x	8	area
Loafing Lot Management									0	area
Manure Incorporation Low Disturbance Late	x	x	x	x	x		x		6	area

	Greensboro watershed Agriculture Load Source (ALS)									
Reclassified agricultural BMP variants	**“DC”**	**“Soy”**	**“OAg”**	**“SmGG”**	**“GM”**	**“Gr”**	**“SM”**	**“Sil”**	**Total ALS affected by BMP**	**Unit**
Manure Injection	x	x	x	x	x		x		6	area
Nutrient Management Core N	x	x	x	x	x	x	x	x	8	area
Nutrient Management Core P	x	x	x	x	x	x	x	x	8	area
Nutrient Management N Placement	x	x	x	x	x	x	x	x	8	area
Nutrient Management N Rate	x	x	x	x	x	x	x	x	8	area
Nutrient Management N Timing	x	x	x	x	x	x	x	x	8	area
Nutrient Management P Placement	x	x	x	x	x	x	x	x	8	area
Nutrient Management P Rate	x	x	x	x	x	x	x	x	8	area
Off Stream Watering Without Fencing									0	area
Precision Intensive Rotational/Prescribed Grazing									0	area
Soil Conservation and Water Quality Plans	x	x	x	x	x	x	x	x	8	area
Tillage Management-Conservation	x	x	x	x	x	x	x	x	8	area
Tillage Management-Continuous High Residue	x	x	x	x	x	x	x	x	8	area
Tillage Management-Low Residue	x	x	x	x	x	x	x	x	8	area
Tree Planting	x	x	x	x	x	x	x	x	8	area
Water Control Structures	x	x	x	x	x	x	x	x	8	area
Wetland Creation - Floodplain	x	x	x	x	x	x	x	x	8	area
Wetland Creation Upland	x	x	x	x	x	x	x	x	8	area
Wetland Rehabilitation Upland	x	x	x	x	x	x	x	x	8	area
Wetland Restoration - Floodplain	x	x	x	x	x	x	x	x	8	area
Wetland Restoration Upland	x	x	x	x	x	x	x	x	8	area
Total reclassified Ag BMP groups applied to load source	31	30	30	31	30	28	30	28		

Table D2. The number of agricultural load sources (ALS) affected by BMP variants are provided in the table. The "x" denotes the application of an agricultural BMP variant onto an agricultural load source in the Greensboro watershed. This level of detail means the reduction capacity of a BMP could vary depending on the load source. Abbreviations: "**P**" = pasture, "**OS**" = agricultural open space, "**NPF**" = non-permitted feeding space, "**PF**" = permitted feeding space, "**LH**" = Leguminous Hay, "**OH**" = Other hay, "**SCH**" = specialty crop high, "**SCL**" = Specialty Crop Low, "**Ttl DLS**" = total develop load source categories affected by Development BMP variants, "Units" indicate the common measurement of development BMP variants.

	Greensboro watershed Agriculture Load Source (ALS)									
Agriculture BMP variants	**P**	**OS**	**NPF**	**PF**	**LH**	**OH**	**SCH**	**SCL**	**Total ALS affected by BMP**	**Unit**
Alternative Crops									0	area
Barnyard Runoff Control			x	x					2	area
Cover Crop Commodity Normal									0	area
Cover Crop Traditional									0	area
Forest Buffer					x	x	x	x	4	area
Forest Buffer Nitrogen Upland	x	x			x	x	x	x	6	area
Forest Buffer Phosphorus and Sediment Upland	x	x			x	x	x	x	6	area
Forest Buffer-Narrow with Exclusion Fencing	x								1	area
Forest Buffer-Streamside with Exclusion Fencing	x								1	area
Forest Buffer-Streamside with Exclusion Fencing Nitrogen Upland	x								1	area
Forest Buffer-Streamside with Exclusion Fencing Phosphorus and Sediment Upland	x								1	area
Grass Buffer					x	x	x	x	1	area
Grass Buffer Nitrogen Upland	x	x			x	x	x	x	1	area
Grass Buffer Phosphorus and Sediment Upland	x	x			x	x	x	x	1	area
Grass Buffer-Narrow with Exclusion Fencing	x								1	area
Grass Buffer-Streamside with Exclusion Fencing	x								1	area
Grass Buffer-Streamside with Exclusion Fencing Nitrogen Upland	x								1	area
Grass Buffer-Streamside with Exclusion Fencing Phosphorus and Sediment Upland	x								1	area
Horse Pasture Management	x								1	area
Land Retirement to Ag Open Space									0	area
Land Retirement to Pasture									0	area
Loafing Lot Management			x	x					2	area
Manure Incorporation Low Disturbance Late									0	area
Manure Injection									0	area
Nutrient Management Core N	x				x	x	x	x	5	area
Nutrient Management Core P	x				x	x	x	x	5	area
Nutrient Management N Placement					x	x	x	x	4	area

Agriculture BMP variants	Greensboro watershed Agriculture Load Source (ALS)									
	P	OS	NPF	PF	LH	OH	SCH	SCL	Total ALS affected by BMP	Unit
Nutrient Management N Rate					x	x	x	x	4	area
Nutrient Management N Timing					x	x	x	x	4	area
Nutrient Management P Placement					x	x	x	x	4	area
Nutrient Management P Rate					x	x	x	x	4	area
Off Stream Watering Without Fencing	x								1	area
Precision Intensive Rotational/Prescribed Grazing	x								1	area
Soil Conservation and Water Quality Plans	x	x			x	x	x	x	6	area
Tillage Management-Conservation									0	area
Tillage Management-Continuous High Residue									0	area
Tillage Management-Low Residue									0	area
Tree Planting	x	x			x	x	x	x	6	area
Water Control Structures					x	x	x	x	4	area
Wetland Creation - Floodplain	x	x			x	x	x	x	6	area
Wetland Creation Upland	x	x			x	x	x	x	6	area
Wetland Rehabilitation Upland	x	x			x	x	x	x	6	area
Wetland Restoration - Floodplain	x	x			x	x	x	x	6	area
Wetland Restoration Upland	x	x			x	x	x	x	6	area
Total reclassified Ag BMP groups applied to load source	24	11	2	2	21	21	21	21		

Table D3. The number of development load sources affected by best management practices variants is provided. Abbreviations: "**MS4B**" = MS4 Buildings and Other, "**MS4R**" = MS4 Roads, "**MS4TCI**" = MS4 tree canopy over Impervious, "**MS4TCT**" = MS4 tree canopy over turf grass, "**MS4TG**" = MS4 turf grass, "**NRB**" = Non-regulated buildings and other, "**NRR**" = Non-Regulated Roads, "**NRTCI**" = non-regulated tree canopy over impervious, "**NRTCT**" = non-regulated tree canopy over turf grass, "**NRTG**" = non-regulated turf grass, "**RC**" = regulated construction, "**Ttl DLS**" = total develop load source categories affected by Development BMP variants, "Units" indicate the common measurement of development BMP variants.

	Greensboro watershed Development Load Source (DLS)												
Development BMP variants	**MS4B**	**MS4R**	**MS4TCI**	**MS4TCT**	**MS4TG**	**NRB**	**NRR**	**NRTCI**	**NRTCT**	**NRTG**	**RC**	**Ttl DLS**	**Unit**
Advanced Sweeping Technology - 1 pass/12 weeks							x					1	area
Bioretention/raingardens - A/B soils, underdrain	x	x	x	x	x	x	x	x	x	x		10	area
Bioretention/raingardens - C/D soils, underdrain	x	x	x	x	x	x	x	x				8	area
Bioswale	x	x	x	x	x	x	x	x	x	x		10	area
Dry Detention Ponds and Hydrodynamic Structures	x	x	x	x	x	x	x	x	x	x		10	area
Dry Extended Detention Ponds	x	x	x	x	x	x	x	x	x	x		10	area
Erosion and Sediment Control Level 1											x	1	area
Erosion and Sediment Control Level 2											x	1	area
Filtering Practices	x	x	x	x	x	x	x	x	x	x		10	area
Forest Buffer					x					x		2	area
Forest Planting					x					x		2	area
Infiltration Practices w/ Sand, Veg. - A/B soils, no underdrain	x	x	x	x	x	x	x	x	x	x		10	area
Infiltration Practices w/o Sand, Veg. - A/B soils, no underdrain	x	x	x	x	x	x	x	x	x	x		10	area
Nutrient Management Maryland Commercial Applicators				x	x				x	x		4	area
Nutrient Management Maryland Do It Yourself				x	x				x	x		4	area
Nutrient Management Plan				x	x				x	x		4	area

	Greensboro watershed Development Load Source (DLS)												
Development BMP variants	**MS4B**	**MS4R**	**MS4TCI**	**MS4TCT**	**MS4TG**	**NRB**	**NRR**	**NRTCI**	**NRTCT**	**NRTG**	**RC**	**Ttl DLS**	**Unit**
Nutrient Management Plan High Risk Lawn				x	x				x	x		4	area
Permeable Pavement w/o Sand, Veg. - A/B soils, no underdrain	x	x	x	x	x	x	x	x	x	x		10	area
Stormwater Performance Standard-Runoff Reduction	x	x	x	x	x	x	x	x	x	x		10	area
Stormwater Performance Standard-Stormwater Treatment	x	x	x	x	x	x	x	x	x	x		10	area
Tree Planting - Canopy					x					x		2	area
Urban Forest Buffer Upland	x	x	x	x	x	x	x	x	x	x		10	area
Vegetated Open Channels - A/B soils, no underdrain	x	x	x	x	x	x	x	x	x	x		10	area
Wet Ponds and Wetlands	x	x	x	x	x	x	x	x	x	x		10	area
Total reclassified Development BMP groups applied to Load Source	14	14	14	18	21	14	15	14	17	20	2		

Table D4. The number of natural load sources affected by BMPs is provided in the table. Abbreviations: "**Ttl DLS**" = total develop load source categories affected by Development BMP variants, "Units" indicate the common measurement of development BMP variants.

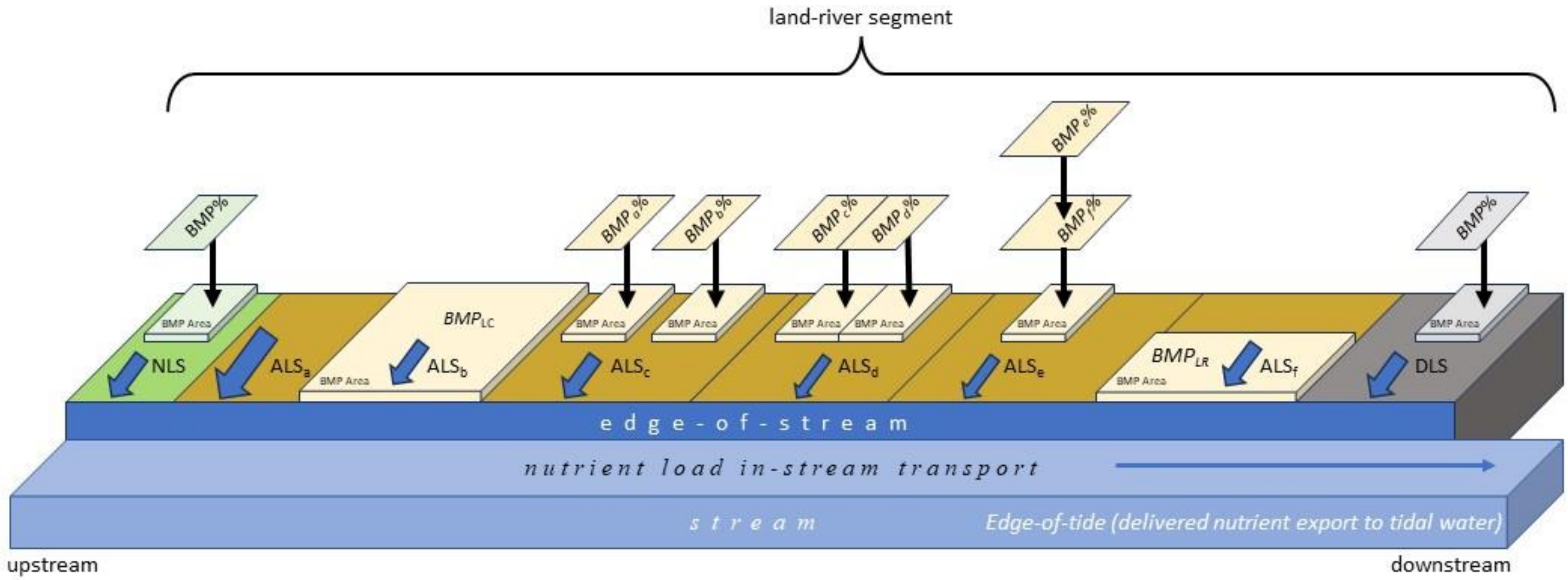
	Greensboro watershed Natural Load Source					
Natural BMP variants	**Harvested Forest**	**Headwater or Isolated Wetland**	**Non-tidal Floodplain Wetland**	**Stream Bed and Bank**	**Total Natural Load Source affected by BMP**	**Unit**
Forest Harvesting Practices	x				1	area
Non-Urban Stream Restoration				x	1	length
Wetland Rehabilitation		x	x		2	area
Total reclassified Natural BMP groups applied to Load Source	1	1	1	1		

E Overview of CAST land-based BMP effectiveness calculations

The BMP effectiveness is the nutrient export (kg) after all BMPs are credited in a sector. CAST calculates nutrient load in an orderly sequence, summarized in Table E. Before efficiencies are credited in a sector, animal BMlPs and BMPs that can change the nutrient load by land use conversion are applied first. Next, efficiency BMPs are applied in one of three ways: total efficiency for a *single load source*, aggregate efficiency of *mutually exclusive BMPs* (two or more BMPs that cannot occupy the same spatial area, such as forest buffer and cover crops), and *overlapping BMPs* (two or more BMPs apply to the same site such as nutrient management, conservation tillage, and cover crops), are combined with any previous efficiency calculations (Fig. E). After crediting efficiencies, CAST quantifies the *pass-through value* defined as the amount of nutrients not intercepted by BMPs. Lastly, any load reduction BMPs are applied to the pass-through value. The nutrient export after crediting load reduction BMPs equals the sector's BMP effectiveness.

Table E. An overview of the orderly sequence used in CAST to calculate the total efficiency of all BMPs. Abbreviation: "Seq" = order of BMP credits, "BMP type" is load source conversion, efficiency, or load reduction. Italicized text is described in the Glossary.

Seq	BMP credit type	Explanation
1.	Account for *load source conversion* BMPs, including animal BMPs.	Since Animal and Load Source BMPs can alter load sources available for other BMPs. They are credited prior to efficiency BMPs.
2.	Calculate the total efficiency of all BMPs for a *single load source*.	$BMP_{ab}\ \% = BMP_a + BMP_b$ $Area_A$ = area occupied by BMP_a $Area_B$ = area occupied by BMP_b
3.	Calculate the aggregate efficiency of *mutually exclusive* BMPs	$BMP_{cd}\% = [(Area_c/Area_{cd}) \times BMP_c\%] + [(Area_d/Area_{cd}) \times BMP_d\%)]$
4.	Next, the *overlapping BMPs* are combined with the previously calculated efficiencies.	$BMP_{ef}\% = 1 – ([1 - BMP_e\%] \times [1 - BMP_f\%])$
5.	*Load reduction* BMPs are credited last.	Deduct nutrients from the pass-through value,. The pass-through value is the amount of nutrients not intercepted by BMPs and is calculated for N, P, and TSS loads after all efficiencies are credited in the land-river segment.



ALS_a = Agricultural load source variant without BMP
ALS_b = Agricultural *load source conversion BMP* changes the agricultural land use to a land use that has a lower nutrient load.
ALS_c = Agricultural load source variant with two or more *single load source BMPs* resulting in nutrient reduction (%).
ALS_d = Agricultural load source variant with two *mutually exclusive BMPs* resulting in nutrient reduction (%). Mutually exclusive BMPs cannot physically occupy the same land area.
ALS_e = Agricultural load source variants with two *overlapping BMPs resulting* in a conversion from a higher load source to a lower source followed by nutrient reduction (%). Overlapping BMPs can apply to the same land area.
ALS_f = Agricultural load source variant with BMP resulting in overall nutrient reduction

BMP% = BMP results in nutrient efficiency
BMP_{LC} = BMP results in load source conversion
BMP_{LR} = BMP results in load source reduction
DLS = Development sector load source
EOS = Edge of stream loads for each sector represents the nutrient load exported from the land to a waterbody due to BMP actions, not local land-river segment conditions.
EOT = Edge-of-tide nutrient loads for each sector represent the nutrient load that actually reaches tidal waters, aka "delivered loads", after applying local land-river segment conditions.
NLS = Natural sector load source

Figure E. The nutrient load for each sector (natural – "NLS", agricultural – "ALS", and development – "DLS") accounts for the nutrient loads from load source areas without BMPs and BMP-impacted areas. Before efficiencies are credited in a sector, animal BMPs and BMPs that can change the nutrient load by land use conversion are applied first (ALS_b). Next, efficiency BMPs are applied in one of three ways: efficiency for a *single load source* (ALS_c), aggregate efficiency of *mutually exclusive BMPs* (ALS_d, two or more BMPs that cannot occupy the same site such as forest buffer and cover crops), and *overlapping BMPs* (ALS_e, two or more BMPs apply to the same spatial area such as nutrient management, conservation tillage, and cover crops), are combined with any previous efficiency calculations. After crediting efficiencies, CAST quantifies the *pass-through value* defined as the amount of nutrients not intercepted by BMPs. Lastly, any *load reduction BMPs* are applied to the pass-through value (ALS_f). The nutrient export after crediting load reduction BMPs equals the sector's BMP effectiveness.

F Pre and Post TMDL t-test comparisons

Table F1. Natural BMPs and Management Plans. Summary of t-test comparisons between pre-TMDL (1985-2010) and post-TMDL (2011-2021) mean groups. Unless otherwise denoted (*), the summary of mean comparisons is between pre-TMDL (1985-2010) and post-TMDL (2011-2021) since the Chesapeake Bay TMDL approval in December 2010. Abbreviations: “Figure Panel” identifies the figure and panel of the corresponding comparisons, “$\bar{x}$ pre- and $\bar{x}$ post-TMDL” represent the mean group comparisons within a range of progress years, “Unit” represents the measurement unit of mean groups, “p” represents the t-test p-value, and “Interpretation” explains the significance of the t-test comparison.

Figure Panel	$\bar{x}$ pre-TMDL	$\bar{x}$ post-TMDL	Unit	p	Interpretation
2a	n/a	2011-2014: 34 ± 3.6 2015-2021: 78 ± 0.2	m	n/a	*All **non-urban stream restoration** projects occurred in the Caroline County portion of the Greensboro watershed after the TMDL.
2b	51 ± .3	62 ± 4.5	ha	0.05	*The mean area covered by **forest harvesting** practices during 2010-2021 is marginally greater than the mean area between 1991-2009 by a factor of 1.2.

Table F2. Septic system and rural-urban development BMPs. Summary of t-test comparisons between pre-TMDL (1985-2010) and post-TMDL (2011-2021) mean groups. Unless otherwise denoted (*), the summary of mean comparisons is between pre-TMDL (1985-2010) and post-TMDL (2011-2021) since the Chesapeake Bay TMDL approval in December 2010. Abbreviations: "Figure Panel" identifies the figure and panel of the corresponding comparisons, "$\bar{x}$ pre- and $\bar{x}$ post-TMDL" represent the mean group comparisons within a range of progress years, "Unit" represents the measurement unit of mean groups, "p" represents the t-test p-value, and "Interpretation" explains the significance of the t-test comparison.

Figure Panel	$\bar{x}$ pre-TMDL	$\bar{x}$ post-TMDL	Unit	p	Interpretation
3a	0.6 ± 0.07	146 ± 21.2	septic systems	< 0.001	The mean number of **septic system connections to public wastewater treatment facilities** is significantly greater after the TMDL compared to 1986-2010 by a factor of 232.
3b	1.4 ± 0.23	41 ± 7.25	septic systems	< 0.001	The mean number of **conventional denitrification systems** is significantly greater after the TMDL compared to 1986-2010 by a factor of 29.
3c	1.5 ± 0.49	341 ± 86.5	number of tanks	< 0.001	The number of **septic tanks pumped** in Kent County increased significantly from 2011 to 2021 compared to 1986-2010 by a factor of 227.
3d	139 ± 38	513 ± 61	ha	< 0.001	The mean area covered by **rural-urban nutrient management plans** after the TMDL is significantly greater compared to the progress years 2001-2010 by a factor of 3.7.
3e	0.007 ± 0.002	0.81 ± 0.08	ha	< 0.001	*The area affected by **tree planting** and **forest buffer** between 2015 and 2021 was significantly greater than between 1995 and 2014 by a factor of 116.
3f	31 ± 5	13.7 ± 7.3	ha	0.06	A comparison of areas affected by **erosion and sediment control** and **street sweeping** displayed marginal significance. Pre-TMDL areas were marginally greater than post-TMDL areas by a factor of 2.3.
3g	21.6 ± 3.5	224 ± 7.8	ha	< 0.001	*A comparison of areas affected by **wetlands and wet/dry ponds in the Delaware portion** of the Greensboro watershed revealed the mean area between 2010 and 2021 was significantly greater than between 1986 and 2009 by a factor of 10. There is no significant difference in the area affected by **dry/wet ponds and wetlands** before and after the TMDL in the Maryland portion of the Greensboro watershed.
3h	14 ± 1.8	24 ± 2	ha	< 0.001	*The area treated by **infiltration and filtration** practices between 2009 and 2021 was significantly greater than between 1991 and 2008 by a factor of 1.7.
3i	145 ± 9.4	61 ± 14.2	ha	< 0.001	Between 1987-2010, the mean of areas treated by **stormwater management practices** was significantly greater than after the TMDL by a factor of 2.4.

Table F3. Agricultural BMPs: Barnyard and loafing, pasture and croplands, and tillage. Summary of t-test comparisons between pre-TMDL (1985-2010) and post-TMDL (2011-2021) mean groups. Unless otherwise denoted (*), the summary of mean comparisons is between pre-TMDL (1985-2010) and post-TMDL (2011-2021) since the Chesapeake Bay TMDL approval in December 2010. Abbreviations: "Figure Panel" identifies the figure and panel of the corresponding comparisons, "$\bar{x}$ pre- and $\bar{x}$ post-TMDL" represent the mean group comparisons within a range of progress years, "Unit" represents the measurement unit of mean groups, "p" represents the t-test p-value, and "Interpretation" explains the significance of the t-test comparison.

Figure Panel	**$\bar{x}$ pre-TMDL**	**$\bar{x}$ post-TMDL**	**Unit**	**p**	**Interpretation**
4a	0.032 ± 0.007	0.49 ± 0.4	km^2	< 0.001	**Off-stream watering** increased significantly post-TMDL approval compared to 1994 to 2010 by a factor of 15.
4b	0.006 ± 0.003	0.13 ± 0.01	km^2	< 0.001	**Loafing lot management and Barnyard runoff control** increased after TMDL significantly by a factor of 22 (p < 0.001). **Loafing lot management** BMPs (0.001 ± 0.00008 km^2 y^{-1}) increased significantly between 2011 and 2021 compared to the mean (0.0003 ± 0.001 km^2 y^{-1}) from 1995 to 2010 by a factor of 3 (p < 0.001). **Barnyard runoff control** BMPs (0.13 ± 0.01 km^2 y^{-1}) increased significantly between 2011 and 2021 compared to the mean (0.006 ± 0.003 km^2 y^{-1}) from 1993 to 2010 by a factor of 22 (p < 0.001).
4c	0.006 ± 0.0008	0.06 ± 0.006	km^2	0.002	**Precision intensive rotational/prescribed grazing** increased significantly between 2011 and 2021 compared to 2009 – 2010 by a factor of 10 (p = 0.002). Management practices applied to **management practices for horse pasture** averaged 0.009 ± 0.002 km^2 y^{-1} post TMDL.
4d	5 ± 0.9	37 ± 4	km^2	< 0.001	The **cover crop + commodity cover crop** mean area is significantly greater after the TMDL than from 1999 to 2010 by a factor of 7.4. The mean area covered by **traditional cover crops without commodity** species after 2011 (29 ± 4 km^2 y^{-1}) is significantly greater than the mean (4 ± 0.6 km^2 y^{-1}) from 1999 through 2010 by a factor of 7.25 (p < 0.001). **Commodity cover crops without traditional** species' mean area (8 ± 1.2 km^2 y^{-1}) after 2011 is significantly greater than the mean (2 ± 0.6 km^2 y^{-1}) from 2006 to 2010 by a factor of 4 (p = 0.004).
4e	n/a	7 ± 1	km^2	n/a	***Manure incorporation and injection** occurred after the TMDL in Caroline and Queen Anne's County portion of the Greensboro watershed between 2013 and 2021.
4f	0.09 ± 0.02	2.7 ± 0.7	km^2	< 0.001	**Water control structures** increased significantly between 2011 and 2021 compared to 1985 to 2010 by a factor of 30.
4g	19 ± 0.83	51 ± 2.3	km^2	< 0.001	*Applications of **high tillage** increased significantly between 2014 and 2021 than during 1989-2013 by a factor of 2.7.
4h	4.7 ± 0.62	37 ± 2.2	km^2	< 0.001	*The **conservation tillage** area was significantly greater between 2014 and 2021 than during 1989-2013 by a factor of 7.9.
4i	7.1 ± 0.7	25 ± 0.09	km^2	< 0.001	*Areas impacted by **low tillage** increased significantly between 2018 and 2021 than from 1994 to 2013 by a factor of 3.5.

Table F4. Summary of t-test comparisons between pre-TMDL (1985-2010) and post-TMDL (2011-2021) mean groups. Unless otherwise denoted (*), the summary of mean comparisons is between pre-TMDL (1985-2010) and post-TMDL (2011-2021) since the Chesapeake Bay TMDL approval in December 2010. Abbreviations: "Figure Panel" identifies the figure and panel of the corresponding comparisons, "$\bar{x}$ pre- and $\bar{x}$ post-TMDL" represent the mean group comparisons within a range of progress years, "Unit" represents the measurement unit of mean groups, "p" represents the t-test p-value, and "Interpretation" explains the significance of the t-test comparison.

Figure Panel	$\bar{x}$ pre-TMDL	$\bar{x}$ post-TMDL	Unit	p	Interpretation
5a	16 ± 2.6	137 ± 39	km^2	< 0.001	*The mean area considered in **nutrient management** BMPs increased significantly between 2012 and 2021 compared to 1999 to 2011 by a factor of 8.6.
5b	23 ± 3.01	89 ± 6.5	km^2	< 0.001	The mean area covered by **agricultural conservation plans** during 2011-2021 is significantly greater than the mean area compared to the progress years 1985-2010 by a factor of 3.9.
5c	0.12 ± 0.02	0.44 ± 0.03	km^2	< 0.001	The average **land retirement (and alternative crop)** area increased significantly post-TMDL compared to pre-TMDL by a factor of 3.7 ($p < 0.001$). **Alternative crop** occurred post TMDL and averaged 0.002 ± 0.0005 $km^2\ y^{-1}$.
5d	0.024 ± 0.0024	0.03 ± 0.002	km^2	0.236	There is no significant difference between pre- and post-TMDL **wetland creation** mean areas.
5e	3.1 ± 1.3	14 ± 0.2	km^2	< 0.001	The average **wetland restoration** area is significantly greater after the TMDL than between 1997 and 2010 by a factor of 4.5.
5f	0.01 ± 0.003	0.20 ± 0.04	km^2	< 0.001	The average **tree planting** area is significantly greater after the TMDL compared to 1986 to 2010 by a factor of 20.
5g	153 ± 46	236 ± 53	km^2	0.298	There is no significant difference between pre- and post-TMDL **forest buffer** mean areas.
5h	10 ± 3.3	49 ± 8.4	km^2	< 0.001	The average **grass buffer** area is significantly greater after the TMDL than during 1985-2010 by a factor of 4.9.
5i	0.01 ± 0.002	0.005 ± 0.002	km^2	0.008	The average area impacted by **exclusionary fencing within the grass and forest buffers** pre-TMDL was significantly greater than the average post-TMDL by a factor of 2. The average area impacted by **exclusionary fencing within the grass** post-TMDL (0.06 ± 0.01) was significantly greater than the average pre-TMDL (0.02 ± 0.004) by a factor of 3 ($p < 0.001$). There was no statistic difference between the average area impacted by **exclusionary fencing within forest buffers** pre-TMDL (0.0006 ± 0.00005) and post-TMDL (0.005 ± 0.002).

Table F5. Summary of t-test comparisons between pre-TMDL (1985-2010) and post-TMDL (2011-2021) mean groups. Unless otherwise denoted (*), the summary of mean comparisons is between pre-TMDL (1985-2010) and post-TMDL (2011-2021) since the Chesapeake Bay TMDL approval in December 2010. Abbreviations: “Figure Panel” identifies the figure and panel of the corresponding comparisons, “$\bar{x}$ pre- and $\bar{x}$ post-TMDL” represent the mean group comparisons within a range of progress years, “Unit” represents the measurement unit of mean groups, “p” represents the t-test p-value, and “Interpretation” explains the significance of the t-test comparison.

Figure Panel	**$\bar{x}$ pre-2011**	**$\bar{x}$ post-2012**	**Unit**	**p**	**Interpretation**
6a	13 ± 1.9	49 ± 5	AU	< 0.001	***Riparian fencing** for livestock is significantly greater between 2010 and 2021 compared to 1986 and 2009 by a factor of 3.8.
6b	798 ± 91	4 135 ± 255	AU	< 0.001	***Mortality composter** BMP is significantly greater between 2010 and 2021 compared to 1988 and 2009 by a factor of 5.2.
6c	12,028 ± 3,158	1,078 ± 346	AU	< 0.001	***Broiler and poultry litter amendments** are significantly greater between 2007 and 2011 compared to 2012 through 2021. Litter amendments declined by 318 AU y^{-1} between 2012 and 2021 (p = 0.0007) by a factor of 11.2.
6d	32,276 ± 3,649	87,374 ± 4,661	AU	< 0.001	***Broiler and poultry waste management** are significantly greater from 2012 to 2021 compared to 1985 through 2011 by a factor of 2.7.
6d	326 ± 14.6	491 ± 10	AU	< 0.001	***Livestock waste management** BMPs are significantly greater between 2012 and 2020 than from 1985 to 2011 by a factor of 1.5.
6e	3,433 ± 1,016	1,265 ± 310	metric tons	0.067	**Poultry manure transport** from pre-TMDL is marginally greater than post TMDL by a factor of 2.7.
6f	472 ± 124	767 ± 734	metric tons	0.64	There is no significant difference between **poultry manure transported** from a county within the Greensboro watershed to a place outside of counties within Greensboro watershed pre (472 ± 124) and post (767 ± 734) TMDL. There is no significant difference between **poultry manure and dairy transport** (946 ± 316) from a county within the Greensboro watershed to another county within the Greensboro watershed pre and post TMDL (p = 0.24).

G Nutrient export comparisions: 2010 versus 2021

Table G1. The land-based load allocations (LA) for edge-of-stream (EOS) nutrient export is comprised of three land river segments forming the Greensboro watershed. The 2010 nutrient export is based on the CAST 2010 progress scenario. The 2021 nutrient export is based on the CAST 2021 progress scenario. Source: CAST loads per unit report and loads report.

	Land-based load allocation: EOS N export (kg y^{-1})			**Land-based load allocation: EOS P export (kg y^{-1})**			**Land-based load allocation: Total suspended solids (Sediment) EOS TSS export (kg y^{-1})**		
Load source per sector	**2010**	**2021**	**diff**	**2010**	**2021**	**diff**	**2010**	**2021**	**diff**
Agriculture sector									
Ag Open Space	50	405	355	9	41	32	118	1,035	917
Double Cropped Land	80,935	27,487	-53,448	1,361	507	-854	681,205	180,609	-500,596
Full Season Soybeans	47,069	88,107	41,038	852	1,714	862	510,964	756,744	245,780
Grain with Manure	116,595	133,733	17,138	1,036	1,189	153	495,739	421,783	-73,956
Grain without Manure	48,855	36,773	-12,082	642	611	-31	316,106	194,566	-121,540
Leguminous Hay	1,569	1,071	-498	27	21	-6	5,829	3,957	-1,872
Non-Permitted Feeding Space	1,074	899	-175	36	37	1	7,643	3,535	-4,108
Other Agronomic Crops	11,366	11,882	516	426	464	38	75,385	64,770	-10,615
Other Hay	5,366	5,815	449	160	305	145	4,306	4,296	-10
Pasture	9,626	7,878	-1,748	826	702	-124	13,420	11,081	-2,339
Silage with Manure	2,780	1,144	-1,636	31	13	-18	23,239	6,377	-16,862
Silage without Manure	235	149	-86	6	2	-4	4,101	1,125	-2,976
Small Grains and Grains	11,799	30,547	18,748	208	499	291	117,505	260,398	142,893
Specialty Crop High	13,650	9,070	-4,580	433	335	-98	158,402	130,434	-27,968
Specialty Crop Low	5,485	3,190	-2,295	611	456	-155	218,912	131,353	-87,559
SumAgriculture	356,454	358,150	1,696	6,664	6,896	232	2,632,874	2,172,063	-460,811

Table G1 (continued). The land-based load allocation (LA) edge-of-stream (EOS) nutrient export comparisons in the Greensboro watershed: 2010 vs 2021.

Load source per sector	Land-based load allocation: EOS N export (kg y^{-1}) 2010	2021	diff	Land-based load allocation: EOS P export (kg y^{-1}) 2010	2021	diff	Land-based load allocation: Total suspended solids (Sediment) EOS TSS export (kg y^{-1}) 2010	2021	diff
Rural-urban development sector									
Non-Regulated Buildings and Other	7,960	8,559	599	262	284	22	117,097	129,346	12,249
Non-Regulated Roads	7,125	7,739	614	223	245	22	83,961	93,653	9,692
Non-Regulated Tree Canopy over Impervious	2,109	2,165	56	66	68	2	16,142	17,030	888
Non-Regulated Tree Canopy over Turf Grass	1,808	1,970	162	127	133	6	10,234	11,415	1,181
Non-Regulated Turf Grass	32,217	32,286	69	2,326	2,250	-76	236,339	244,042	7,703
Sum Development	51,219	52,719	1,500	3,004	2,980	-24	463,773	495,486	31,713
Natural sector									
Harvested Forest	896	846	-50	8	7	-1	1,453	1,370	-83
Headwater or Isolated Wetland	15,332	14,926	-406	350	342	-8	17,124	16,681	-443
Mixed Open	3,057	2,581	-476	183	156	-27	198,277	167,438	-30,839
Non-tidal Floodplain Wetland	1,526	1,525	-1	39	39	0	1,739	1,738	-1
Stream Bed and Bank	26,761	26,982	221	5,201	5,286	85	16,285,221	13,916,209	-2,369,012
True Forest	9,352	9,329	-23	238	238	0	10,645	10,622	-23
Water	3,522	3,483	-39	221	219	-2			
Sum Natural	60,446	59,672	-774	6,240	6,287	47	16,514,459	14,114,058	-2,400,401
Septic systems sector									
Sum Septic systems	19,310	18,874	-436						

Table G2. The land-based load allocations (LA) for edge-of-tide (EOT) nutrient export is comprised of three land river segments forming the Greensboro watershed. The 2010 nutrient export is based on the CAST 2010 progress scenario. The 2021 nutrient export is based on the CAST 2021 progress scenario. Source: CAST loads per unit report and loads report.

	Land-based load allocation: EOT N export (kg y^{-1})			Land-based load allocation: EOT P export (kg y^{-1})			Land-based load allocation: Total suspended solids (Sediment) EOT TSS export (kg y^{-1})		
Load source per sector	**2010**	**2021**	**diff**	**2010**	**2021**	**diff**	**2010**	**2021**	**diff**
Agriculture sector									
Ag Open Space	21	163	142	6	22	16	13	109	96
Double Cropped Land	33,074	11,258	-21,816	802	299	-503	72,047	19,138	-52,909
Full Season Soybeans	19,278	36,014	16,736	514	987	473	54,074	80,086	26,012
Grain with Manure	47,751	54,571	6,820	619	694	75	52,436	44,633	-7,803
Grain without Manure	19,932	15,024	-4,908	380	354	-26	33,435	20,603	-12,832
Leguminous Hay	635	436	-199	17	13	-4	613	417	-196
Non-Permitted Feeding Space	-522	384	906	23	24	1	801	371	-430
Other Agronomic Crops	4,648	4,858	210	258	279	21	7,963	6,842	-1,121
Other Hay	2,203	2,364	161	102	174	72	454	452	-2
Pasture	3,916	3,188	-728	455	381	-74	1,415	1,165	-250
Silage with Manure	1,134	468	-666	19	8	-11	2,459	677	-1,782
Silage without Manure	94	61	-33	3	1	-2	434	119	-315
Small Grains and Grains	4,847	12,454	7,607	127	291	164	12,442	27,549	15,107
Specialty Crop High	5,559	3,739	-1,820	243	198	-45	16,774	13,842	-2,932
Specialty Crop Low	2,219	1,297	-922	326	243	-83	23,151	13,908	-9,243
Sum Agriculture	144,789	146,279	1,490	3,894	3,968	74	278,511	229,911	-48,600

Table G2 (continued). The land-based load allocation (LA) EOT nutrient export comparisons in the Greensboro watershed: 2010 vs 2021.

	Land-based load allocation: EOT N export (kg y^{-1})			Land-based load allocation: EOT P export (kg y^{-1})			Land-based load allocation: Total suspended solids (Sediment) EOT TSS export (kg y^{-1})		
Load source per sector	**2010**	**2021**	**diff**	**2010**	**2021**	**diff**	**2010**	**2021**	**diff**
Rural-urban development sector									
Non-Regulated Buildings and Other	3,217	3,461	244	137	149	12	12,344	13,639	1,295
Non-Regulated Roads	2,889	3,138	249	119	130	11	8,863	9,887	1,024
Non-Regulated Tree Canopy over Impervious	852	875	23	34	36	2	1,701	1,795	94
Non-Regulated Tree Canopy over Turf Grass	727	793	66	66	69	3	1,077	1,202	125
Non-Regulated Turf Grass	13,043	13,071	28	1,242	1,207	-35	24,943	25,764	821
Sum Development load	20,728	21,338	610	1,598	1,591	-7	48,928	52,287	3,359
Natural sector									
Harvested Forest	359	338	-21	4	4	0	152	143	-9
Headwater or Isolated Wetland	6,135	5,974	-161	194	190	-4	1,788	1,741	-47
Mixed Open	1,222	1,032	-190	104	89	-15	20,663	17,452	-3,211
Non-tidal Floodplain Wetland	616	616	0	22	22	0	182	182	0
Stream Bed and Bank	10,862	10,941	79	2,808	2,833	25	1,716,323	1,467,921	-248,402
True Forest	3,777	3,768	-9	137	137	0	1,116	1,114	-2
Water	1,694	1,675	-19	197	195	-2		-	
Sum Natural	24,665	24,344	-321	3,466	3,470	4	1,740,224	1,488,553	-251,671
Septic systems sector									
Sum Septic systems	7,849	7,679	-170						

H Choptank tidal fresh TMDL segment– land-based load allocation TMDL goal

The Bay TMDL comprises 92 smaller TMDLs, and each TMDL is based on a smaller land-river segment in the Chesapeake Bay watershed. I compared the integrated nutrient loads from the Greensboro watershed to the Choptank Tidal Fresh (CHOTF) TMDL segment to assess the impact of historical BMP implementation in the Greensboro watershed and the larger CHOTF segment (Fig. 2.1). The CHOTF TMDL (local TMDL) aims to reduce N, P, and TSS by 24%, 18%, and 7%, respectively, to achieve localized water quality goals in the Choptank River (USEPA 2010g). The N, P, and TSS percent reductions reported in Table H1 indicate TSS reductions in the Greensboro watershed have exceeded the local TSS reduction goal of 7%. In contrast, N and P reductions are far from reaching the land-based load percent reduction goals of the CHOTF TMDL segment.

Table H1. The Choptank Tidal Fresh (CHOTF) TMDL segment is made up of land-based load allocations (LA) and waste load allocations (LA). The nutrient reduction goals are based on the 2009 baseline conditions. These allocations are calculated as delivered loads, the nutrient export that reaches tidal waters annually (USEPA 2010g). The atmospheric deposition load allocation (15,139 kg) is not included in the N reduction goal of 24%. Additional N reduction to tidal waters via air deposition is achieved by implementing federal air regulations. (USEPA 2010a, 2010e).

CHOTF TMDL	**N kg y^{-1}**	**P kg y^{-1}**	**TSS kg y^{-1}**
Reduction (%)	24	18	7
2009 baseline conditions	841,770	85,722	12,618,723
TMDL	638,848	70,419	11,676,769
WLA	19,772	3,121	736,332
Land-based (LA)	619,076	67,299	10,940,437

Another comparison between 2021 edge-of-tide loads in the Greensboro watershed and the Choptank Tidal Fresh (CHOTF) LA reveals the load sources in the Greensboro watershed contribute 8% N, 10% P, and 9% TSS of the total respective nutrient export generated in the

CHOTF. The Greensboro watershed nutrient export is relatively small given that the Greensboro watershed is 36% of the CHOTF area and comprises 23% agriculture, 29% development, and 36% natural resources of the total respective land cover areas in the CHOTF (Fig. 2.1). The data in Table H2 indicates that CHOTF areas outside of the Greensboro watershed contribute much more of the nutrient export and that the agriculture sector within and outside of the Greensboro watershed is the prevailing source of N and P. The N export is greatest from the agriculture sector due to increased N fertilizer applications in recent decades, and the continued N fertilizer application onto cropland is projected to accumulate within the Choptank River basin, contributing more to the catchment N export (Chang et al. 2021).

Table H2. Nutrient export based on land-based LA after BMP implementation in 2021 in the Choptank Tidal Fresh TMDL segment and the Greensboro watershed. Abbreviations: “CHOTF 2021 BMP action EOT export (kg y^{-1})” represents the total edge of tide (EOT) nutrient export due to BMP implementation in progress year 2021, “Greensboro watershed 2021 BMP action EOT export (kg)” represents the total edge of tide nutrient export due to BMP implementation in progress year 2021, “Greensboro watershed Percentage of CHOTF export” represents the percentage of CHOTF nutrient export from the Greensboro watershed, “CHOTF TMDL LA (kg y^{-1})” represents the TMDL land-based load allocation for the CHOTF, and “Nutrient reduction (kg y^{-1})” is the amount of N, P, and TSS reduction needed to reach the CHOTF TMDL.

Nutrient by sector	CHOTF 2021 BMP action EOT export (kg y^{-1})	Greensboro watershed 2021 BMP action EOT export (kg y^{-1})	Greensboro watershed Percentage of CHOTF export	CHOTF TMDL LA (kg y^{-1})	Nutrient reduction (kg y^{-1})
N sector					
Agricultural TN	2,106,994	146,279	7%		
Development TN	201,535	21,338	11%		
Natural TN	213,687	24,344	11%		
Septic TN	75,930	7,679	10%		
SumTN	2,598,147	199,640	8%	619,076	1,979,071
P sector					
Agricultural TP	52,044	3,968	8%		
Development TP	12,706	1,591	13%		
Natural TP	27,308	3,470	13%		
Sum TP	92,058	9,029	10%	67,299	24,759
TSS sector					
Agricultural TSS	3,505,229	229,911	7%		
Development TSS	607,898	52,287	9%		
Natural TSS	16,399,805	1,488,553	9%		
Sum TSS	20,512,932	1,770,751	9%	10,940,437	9,572,495

The data also show that sediment export from the CHOTF segment is higher than the local TMDL, indicating that much more is needed to curtail loads from stream beds and banks to lessen the sediment loads from the natural sector. Based on the data, a 76%, 27%, and 47% reduction in N, P, and TSS are needed to achieve the CHOTF land-based TMDL, and further reductions in the Greensboro watershed could improve water quality in the Choptank River.

I Nutrient inputs and receiving land area

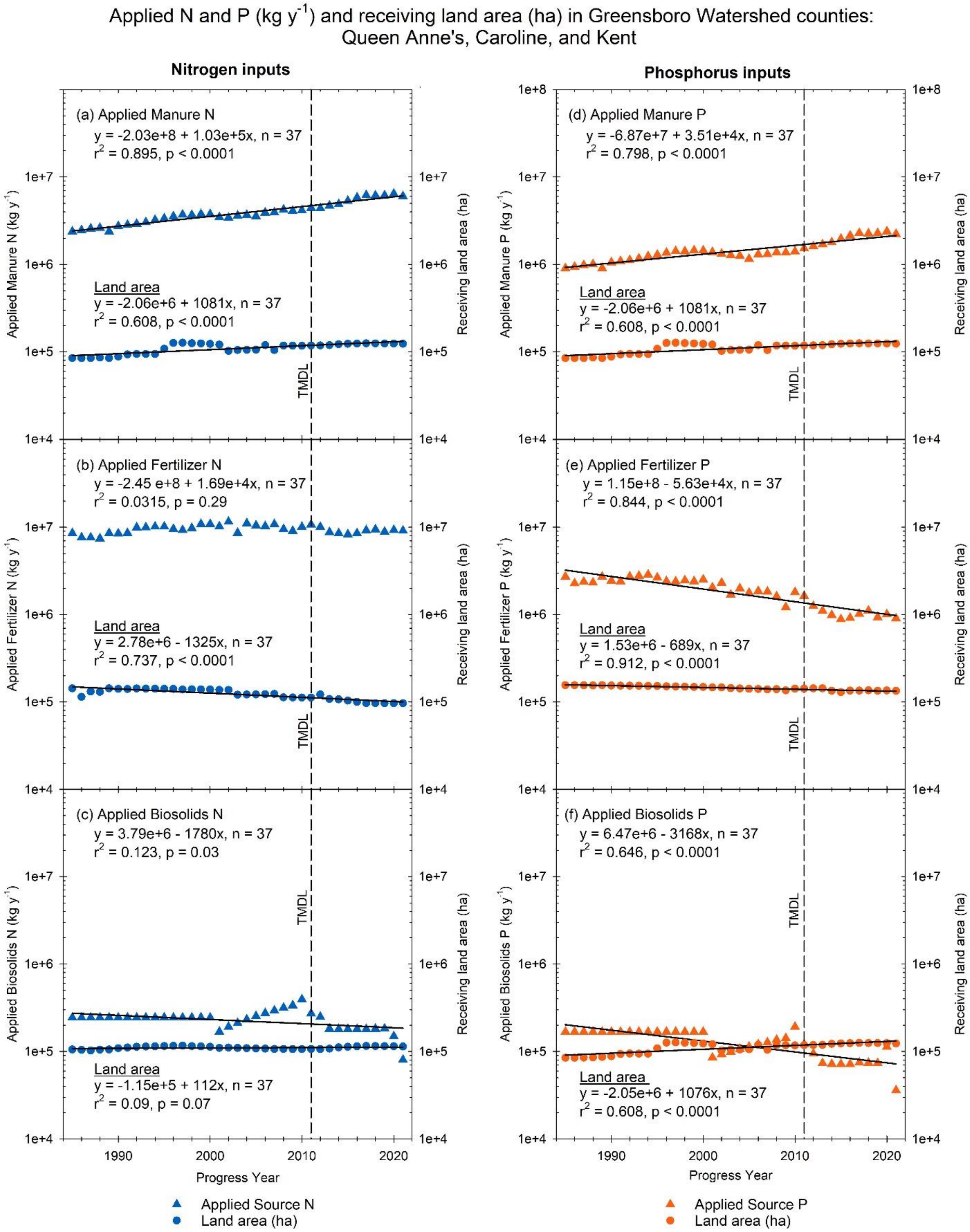


Figure I1. Applied N and P from manure, fertilizer, and biosolids in Caroline and Queen Anne’s Counties, MD, and Kent County, DE. Manure applications continue to increase as fertilizer and biosolid decrease.

J Agricultural best management practices

Table J1. Few cover crop review papers report its N or P efficiency.

Cover crop impacts on --	N or P Efficiency reported	Spatial extent	Reference
Water quality management	N and P efficiencies: Quantitative	Upper Mississippi River Basin	Christianson et al. (2017b)
Soil microorganisms in P cycling through agroecosystems	P efficiency: Qualitative	Global	Hallama et al. (2018)
Nitrogen leaching, net greenhouse gas balance, and crop productivity	n/a	Global	Abdalla et al. (2019)
Trends, programs, and on-farm management practices	n/a	United States	Wallander et al. (2021)
Conservation tillage and soil health	n/a	Southeastern U.S.	Farmaha et al. (2022)
Soil properties	n/a	Global	Koudahe et al. (2022)
Soil erosion and quality, nitrate leaching, carbon sequestration, mineral fertilizer requirement, nutrient and water competition with cash crops, and management and interest in farm economics	n/a	Europe	Rivière et al. (2022)

Table J2. Factors contributing to wide efficiency ranges include geography and BMP type. Case studies of single types of agricultural BMP efficiencies demonstrated variability worldwide. Examples of four studies that evaluated the singular nutrient reduction efficiency of multiple BMPs (multi-BMPs) resulted in BMP efficiencies <50%. Each multi-BMP study is composed of a unique mix of agricultural BMPs. **Multi-BMPs 1**: decreased P fertilization, vegetated buffer strips along streams and constructed wetlands in the waterways, no autumn tilling, and removing point TP sources from scattered dwellings. **Multi-BMPs 2**: filter strips, grassed waterways, constructed wetlands, detention basins, farmland conversion to a forest, soil nutrient management, conservation tillage, contour farming, and strip cropping. **Multi-BMPs 3**: 30% fertilizer reduction, no-tillage, and terracing. **Multi-BMPs 4:** land retired from grain production, fertilizer cessation, wetlands, and buffers. **Multi-BMPs 5**: winter/spring cover crops, constructed wetlands, and buffer strips.

	Nutrient Reduction			
BMP	**Nitrogen (%)**	**Phosphorus (%)**	**Country**	**Reference**
Conservation tillage	TN: 8.99	TP: 7	China	Liu et al. (2013)
	TN: 68	TP: 12	Canada	Tiessen et al. (2010)
Cover crops	TN: 25 - 96		U.S.	Hively et al. (2020)
	NO_3: 15.2-18.8		Japan	Sith et al. (2019)
	NO_3-N: 61		U.S.	Kaspar et al. (2007)
	NO_3: 45		U.S.	Staver et al. (1998)
Riparian buffer	NO_3: 42 -100		Canada	Hill et al. (2014)
	NO_3: 90 -100		Italy	Balestrini et al. (2011)
Vegetative filter strips	org. N: 31.4 - 42.5 NO_3: 29.3 – 36.1	org. P: 34.6- 42	India	Himanshu et al. (2019)
	NO_3^--N: 34 NH_4^+-N: 58	TP: 66	China	Lin et al. (2003)
		TP: 31 -89	Canada	Abu-Zreig et al. (2003)
	TN: 39-81 NO_3-N: 47-98	TP: 40-91 PO_4-P: 39-90	U.S.	Chaubey et al. (1995)
		TP: 61	U.S.	Dillaha et al. (1989)
Multi-BMPs 1		TP: 26	Norway	Engebretsen et al. (2019)
Multi-BMPs 2	TN: 1.03-38.40	TP: 1.36-39.34	China	Qiu et al. (2019)
Multi-BMPs 3	TN: 8.0 NO_3: 8.6	TP: 11.1	Turkey	Özcan et al. (2017)
Multi-BMPs 4	NO_3-N: 90		U.S.	Bunnell-Young et al. (2017)
Multi-BMPs 5	TN: 30	TP: 20	Sweden	Arheimer et al. (2005b)

Table J3. Agricultural TN and TP load reduction (%). Abbreviations: "Province" represents the average TN in the Chesapeake Bay watershed (All) and the average TN and TP efficiencies in the Coastal Plain Province within the Chesapeake Bay watershed (CP). Adapted from Simpson et al. 2009.

Province	Agricultural BMP Classification	TN %	TP %
All	**Conservation Plans**		
	Conventional tillage	8	15
	Conservation tillage	3	5
	Hayland	3	5
	Pastureland	5	10
	Conservation tillage	8	22
CP	**Cover Crops**		
	Drilled Rye early	45	15
	Drilled Rye normal	41	7
	Drilled Rye late	19	0
	Other Rye early	38	15
	Other Rye normal	35	7
	Other Rye late	16	0
	Aerial/soy Rye early	31	15
	Aerial/corn Rye early	18	15
	Drilled Wheat early	31	15
	Drilled Wheat normal	29	7
	Drilled Wheat late	13	0
	Other Wheat early	27	15
	Other Wheat normal	24	7
	Other Wheat late	11	0
	Aerial/soy Wheat early	22	15
	Aerial/corn Wheat early	13	15
	Drilled Barley early	38	15
	Drilled Barley normal	29	7
	Other Barley early	32	15
	Other Barley normal	24	7
	Aerial/soy Barley early	27	15
	Aerial/corn Barley early	15	15
All	**Dairy Feed Management**		
	*default numbers for when direct measurement not an option	24	25
All	**Dry Detention Ponds/Basins and Hydrodynamic Structures**	5	10
All	**Dry Extended Detention Basins**	20	20
CP	**Forest Buffer**		
	Inner Coastal Plain	65	42
	Outer Coastal Plain Well Drained	31	45
	Outer Coastal Plain Poorly Drained	56	39
All	**Forest Harvesting**	50	60

Table J3 (continued). Agricultural TN and TP load reduction (%).

Province	Agricultural BMP Classification	TN %	TP %
CP	**Grass Buffer**		
	Inner Coastal Plain	46	42
	Outer Coastal Plain Well Drained	21	45
	Outer Coastal Plain Poorly Drained	39	39
All	**Infiltration and Filtration**		
	Bioretention C/D soils, underdrain	25 +/- 15	45 +/- 20
	Bioretention A/B soils, underdrain	70 +/- 15	75+/- 20
	Bioretention A/B soils, no underdrain	80+/- 15	85+/- 20
	Filters All (sand, organic, peat)	40+/- 15	60+/- 10
	Vegetated Open Channels C/D soils, no underdrain	10+/- 20	10+/- 20
	Vegetated Open Channels A/B soil, no underdrain	45+/- 20	45+/- 20
	Bioswale	70+/- 15	75+/- 20
	Permeable Pavement (no sand/veg) C/D soils, underdrain	10+/- 15	20+/- 20
	Permeable Pavement (no sand/veg) A/B soils, underdrain	45+/- 15	50+/- 20
	Permeable Pavement (no sand/veg) A/B soils, no underdrain	75+/- 15	80+/- 20
	Permeable Pavement (w/ sand/veg) C/D soils, underdrain	20+/- 15	20+/- 20
	Permeable Pavement (w/ sand/veg) A/B soils, underdrain	50+/- 15	50+/- 20
	Permeable Pavement (w/ sand/veg) A/B soils, no underdrain	80+/- 15	80+/- 20
	Infiltration Practices (no sand/veg) A/B soils, no underdrain	80+/- 15	85+/- 15
	Infiltration Practices (w/ sand/veg) A/B soils, no underdrain	85+/- 15	85+/- 10
All	**Mortality Composting**	40	10
All	**Off-Stream Watering with Fencing**	25	30
All	**Off-Stream Watering without Fencing**	15	22
CP	**Wetland Restoration and Creation**		
	Coastal Plain (4% of watershed in wetlands)	25	50

Table J4. Frequently studied agricultural BMPs in the U.S. Coastal Plain Province.

Agricultural BMPs studied in the U.S. Coastal Plain Province	**Number of peer-reviewed studies**
Alternative crop	2
Bioreactor	2
Cover Crops	18
Ditch, drainage maintenance	5
Multiple BMPs	20
No-till, Tillage	5
Nutrient Management	1
On-Farm water storage	1
Poultry litter	5
Riparian buffer	27
Wetland creation or restoration	10
Total	96

K Mann-Whitney test results

Table K1. **Levels of significance for t-test comparisons between spatial scales**. Abbreviations: “App” denotes empirical “E” and model “M” approach, “Variable” lists the classes of variables, “Interpretation” states the significance of the t-test, “n” is the sample size, “t-test” represents the results of the two-tailed p-value (p), t-statistic (t), corresponding degrees of freedom (df), “$\overline{x}$” denotes the mean cover crop N efficiency expressed as a percent, “se” is the standard error, “sd” is the standard deviation, and “Mann-Whitney” represents the Mann-Whitney Rank Sum Test p-value (p) for t-test comparisons that failed the Shapiro-Wilk test ($p<0.05$) normality test, “LQ” equals the 25th percentile, “Mdn” is the median or the 50th percentile, and “UQ” equals the 75th percentile.

				t-test						Mann-Whitney			
App	**Variable**	**Interpretation**	**n**	**p**	**t**	**df**	**$\overline{x}$**	**se**	**sd**	**p**	**LQ**	**Mdn**	**UQ**
	A comparison of spatial scale												
E	Plot (< 0.25 ha)	Plot (E) = Field (E)	473	0.17	-1.39	522	47	1.4	29	0.13	20	47	74
		Plot (E) > Sm. wshd (M)		< 0.001	5.2	25				< 0.001			
E	Field (0.50-20 ha)	Field (E) > Sm. wshd (M)	51	0.01	2.7	61	41	4.5	32	0.09	13	31	76
M	Plot	Plot (M) > Plot (E)	28	< 0.001	7.4	33	79	4.1	22	< 0.001	69	86	97
M	Field	Field (M) = Field (E)	12	0.13	1.54	61	56	6.8	23	0.09	35	53	78
		Field (M) > Sm. wshd (M)		< 0.001	-4.2	31				n/a			
M	Sm. wshd (50 km^2)		21				25	4.1	19		10	21	32
M	Lg. wshd (200-300 km^2)	Lg. wshd (M) > Sm. wshd (M)	104	< 0.001	-7.6	123	62	2.0	21	< 0.001	46	64	80
		Lg. wshd (M) = Field (M)		0.36	0.9	114				0.39			
		Lg. wshd (M) > Plot (M)		< 0.0001	-3.9	130				< 0.001			
		Lg. wshd (M) > Field (E)		< 0.001	4.3	72				< 0.001			
		Lg. wshd (M) > Plot (E)		< 0.001	6.1	130				< 0.001			

Table K2. Levels of significance for t-test comparisons between hydric soils, tillage type, and hydrologic soil groups. Abbreviations: "App" denotes empirical "E" and model "M" approach, "Variable" lists the classes of variables, "Interpretation" states the significance of the t-test, "n" is the sample size, "t-test" represents the results of the two-tailed p-value (p), t-statistic (t), corresponding degrees of freedom (df), "$\overline{x}$" denotes the mean cover crop N efficiency expressed as a percent, "se" is the standard error, "sd" is the standard deviation, and "Mann-Whitney" represents the Mann-Whitney Rank Sum Test p-value (p) for t-test comparisons that failed the Shapiro-Wilk test ($p<0.05$) normality test, "LQ" equals the 25th percentile, "Mdn" is the median or the 50th percentile, and "UQ" equals the 75th percentile.

				t-test						Mann-Whitney			
App	**Variable**	**Interpretation**	**n**	**p**	**t**	**df**	**$\overline{x}$**	**se**	**sd**	**p**	**LQ**	**Mdn**	**UQ**
	A comparison of tillage type												
E	No-till (NT)	NT (E) > Conv (E)	369	0.03	2.2	405	49	1.6	31	0.04	20	52	76
		NT (E) = LT (E)		0.09	-1.9	7.6				0.19			
		NT (E) > Plow (E)		0.03	2.2	409				0.04			
E	Low-till (LT)	LT (E) > Conv (E)	8	0.03	-2.3	44	64	7.5	21	0.03	51	72	79
		LT (E) > Plow (E)		0.02	-2.5	48				0.02			
E	Conventional (Conv)	Conv (E) = Plow (E)	38	0.97	-0.04	78	38	5.0	31	0.74	13	29	65
E	Plowed seedbed (Plow)		42				38	4.3	28		15	29	54
E	Average tillage (NT, Conv)		10				34	7.7	25		15	27	51
M	NT	NT (M) > NT (E)	150	< 0.001	-6.3	374	64	1.8	22	< 0.001	48	66	83
	A comparison of hydric (Y) and non-hydric (N) soils												
E	Y - Hydric		312				45	1.7	30		15	46	72
E	N - Hydric	N - Hydric (E) = Y - Hydric (E)	212	0.235	1.2	522	48	2.0	29	0.202	24	45	76
M	Y - Hydric	Y - Hydric (M) > Y - Hydric (E)	150	< 0.001	6.9	460	64	1.8	22	< 0.001	48	66	83
		Y - Hydric (M) > N - Hydric (M)		< 0.001	-14.6	28				< 0.001			
M	N - Hydric		15				16	2.8	11		7	18	22

Table K2 (continued). Levels of significance for t-test comparisons between hydric soils, tillage type, and hydrologic soil groups.

				t-test						Mann-Whitney			
App	**Variable**	**Interpretation**	**n**	**p**	**t**	**df**	**$\bar{x}$**	**se**	**sd**	**p**	**LQ**	**Mdn**	**UQ**
	A comparison of hydrologic soils group												
E	A	A (E) > A (M)	181	< 0.001	-8.3	32	44	2.0	27	< 0.001	21	45	65
E	B	B (E) > A (E)	260	0.014	2.4	439	51	1.9	31	0.013	23	53	80
E	AB		28				24	4.0	21		8	19	31
E	ABD		45				38	4.7	31		15	28	70
M	A		15				16	2.8	11		7	18	22
M	B	B (M) > AB (E)	28	< 0.001	9.6	54	79	4.1	22	n/a	69	86	97
		B (M) > ABD (E)		< 0.001	6	71				n/a			
		B (M) > B (E)		< 0.001	6.2	40				< 0.001			
		B (M) > A (M)		< 0.001	-10.5	41				< 0.001			
		B (M) > CD (M)		< 0.001	3.5	124				< 0.001			
M	AB		6				42	2.2	5		39	44	46
M	CD	CD (M) > A (M)	98	< 0.001	13.6	34	63	2.1	21	< 0.001	48	66	80
		CD (M) > AB (M)		< 0.001	6.8	17				0.013			

Table K3. **T-test of experimental groups.** Summary of t-test mean and median comparisons between **before-after and control-treatment N efficiency formulae**. Abbreviations: "App" represents empirical (E) and modeling (M) approach, "Group comparison" represents the N efficiency formulae group, "Interpretation" represents the significance of the t-test, "n" represents the sample size, "t-test" represents the results of the two-tailed p-value (p), t-statistic (t), corresponding degrees of freedom (df), "$\overline{x}$" represents the mean cover crop N efficiency, "se" represents the standard error, "sd" represents the standard deviation, and "Mann-Whitney" represents the Mann-Whitney Rank Sum Test p-value (p) for t-test comparisons that failed the Shapiro-Wilk test ($p<0.05$) normality test, "Mdn" represents the 50th percentile, "LQ" represents the 25th percentile, and "UQ" represents the 75th percentile.

				t-test						Mann-Whitney			
App	**Group comparison**	**Interpretation**	**n**	**p**	**t**	**df**	**$\overline{x}$**	**se**	**sd**	**p**	**Mdn**	**LQ**	**UQ**
	<u>Before-after (BA) formulae comparison of N inputs</u>												
E	Prev spring (Sp) fertilizer	Prev fall > Prev Sp	176	<0.001	-10.7	411	29	1.8	24	<0.001	23	8	41
E	Pre fall soil N and groundwater		290				55	1.7	28		57	31	80
	<u>BA Immobilization formulae comparison of N inputs</u>												
E	Prev Sp fertilizer	Prev fall > Prev Sp	176	0.002	3.13	274	29	1.8	24	<0.001	23	8	41
E	Prev fall soil N		100				38	2.4	24		37	18	52
	<u>BA N pathway normalized by previous fall soil N</u>												
E	Numerator: Spring Soil N inv.		163				69	1.7	22		75	56	87
E	Numerator: Sp Immobilization (I)	Spring Soil N > I	100	<0.001	-10.8	261	38	2.4	24	<0.001	37	18	52
E	Numerator: December Soil N	Sp Soil N > December	13	0.07	1.8	174	58	5.1	18	0.03	63	45	73
	<u>Control-treatment (CT) Formulae Comparison</u>												
E	Soil N inventory (inv.)		22				59	6.6	31		72	29	86
M	Soil N inventory	Soil (M) > Soil (E)	14	0.04	-2.13	34	80	6.3	24	0.025	86	66	99
E	Groundwater (Gw)		28				53	5.3	28		49	40	83
M	Gw	Gw (M) > Gw (E)	130	0.03	2.13	156	63	1.9	21	0.08	65	46	81
	<u>All BA vs All CT</u>												
E	Before – After (BA)		466				45	1.4	30		44	18	72
E+M	Control – Treatment (CT)	CT > BA	223	<0.001	-6.2	490	59	1.8	26	<0.001	59	39	82
	<u>Groundwater export (E vs E + M)</u>												
E	Gw (BA)		14				10	2.7	10		5	2	16
E+M	Gw (CT)	Gw (CT) > Gw (BA)	158	<0.001	-16	27	61	1.8	23	<0.001	61	43	81
	<u>Groundwater export (E vs E)</u>												
E	Gw (BA)		14				10	2.7	10		5	2	16
E	Gw (CT)	Gw (CT) > Gw (BA)	28	<0.001	-7.3	38	53	5	28	<0.001	49	40	83

Table K4. **T-test of data collection years**. Significance levels for t-test comparisons between groups of data collection years. Abbreviations: App: “E” represents empirical research, “M” represents modeling research, “Variable” represents the classes of variables, “Interpretation” represents the significance of the t-test, “n” represents the sample size, “t-test” describes the results of the two-tailed p-value (p), t-statistic (t), corresponding degrees of freedom (df), “$\overline{x}$” represents the mean cover crop N efficiency expressed as a percent, “se” represents the standard error, “sd” represents the standard deviation, and “Mann-Whitney” represents the Mann-Whitney Rank Sum Test p-value (p) for t-test comparisons that failed the Shapiro-Wilk test ($p<0.05$) normality test, “LQ” means the 25th percentile, “Mdn” represents the 50th percentile, and “UQ” represents the 75th percentile.

				t-test						**Mann-Whitney**			
App	**Variable**	**Interpretation**	**n**	**p**	**t**	**df**	**$\overline{x}$**	**se**	**sd**	**p**	**LQ**	**Mdn**	**UQ**
	A comparison of data collection years												
E + M	Before 2006	After 2006 > Before 2006	542	< 0.001	-8.38	295	46	1.3	30	< 0.001	19	44	72
E + M	After 2006		147				65	1.9	23		48	68	83
E	Early E: 1987-2002	Early E = Recent E	509	0.274	1.1	522	46	1.3	30	0.272	19	45	74
E	Recent E: 2012-2018		15				55	6.7	26		41	54	79

Table K5. **Consecutive years of cover crop growth**. Significance levels for t-test comparisons between years of consecutive cover crop growth. Abbreviations: "App" denotes empirical "E" and model "M" approach, "Variable" represents the classes of variables, "Interpretation" states the significance of the t-test, "n" means the sample size, "t-test" describes the results of the two-tailed p-value (p), t-statistic (t), corresponding degrees of freedom (df), "$\bar{x}$" represents the mean cover crop N efficiency expressed as a percent, "se" reflects the standard error, "sd" represents the standard deviation, and "Mann-Whitney" represents the Mann-Whitney Rank Sum Test p-value (p) for t-test comparisons that failed the Shapiro-Wilk test ($p<0.05$) normality test, "LQ" means the 25th percentile, "Mdn" is the median or the 50th percentile, and "UQ" represents the 75th percentile.

				t-test						Mann-Whitney			
App	**Variable**	**Interpretation**	**n**	**p**	**t**	**df**	**$\bar{x}$**	**se**	**sd**	**p**	**LQ**	**Mdn**	**UQ**
	A comparison of consecutive years of cover crop growth												
E	1 y		30				35	4.8	26		12	29	45
E	2 y	2 y (E) > 1 y (E)	218	0.001	-3.2	246	54	2.1	31	0.002	26	59	81
		2 y (E) > 3 y (E)		< 0.001	3.5	386				< 0.001			
E	3 y		170				43	2.2	29		13	44	68
E	7 y (Soil N inventory)	7 y (E) > 1 y (E)	12	< 0.001	6.5	40	85	2.4	8	< 0.001	80	85	93
		7 y (E) > 3 y (E)		< 0.001	-5	36				0.001			
		7 y (E) > 9 y (E)		< 0.001	16	24				n/a			
E	9 y (Immobilization)		14				27	2.5	9		20	26	36
E	13 y (Immobilization, I)	13 y (E, I) > 13 y (E, G)	5	< 0.001	4.7	17	41	8.5	19	0.003	26	33	59
		13 y (E, I) > 9 y (E)		0.046	2.1	17				n/a			
E	13 y (Groundwater, G)		14				10	2.7	10		5	2	16
M	2 y	2 y (M) > 2 y (E)	28	< 0.001	-5.5	42	79	4.1	22	< 0.001	69	86	97
M	10 y (Groundwater, G)	10 y (M) > 9 y (E)	92	< 0.001	-7.6	104	66	1.9	19	< 0.001	54	69	81
		10 y (M) > 13 y (E, G)		< 0.001	-11	104				< 0.001			

Table K6. **Significance levels for t-test comparisons between data collection years of legumes and non-legumes**. Abbreviations: “App” denotes empirical “E” and model “M” approach, “Variable” represents the classes of variables, “Interpretation” states the significance of the t-test, “n” means the sample size, “t-test” describes the results of the two-tailed p-value (p), t-statistic (t), corresponding degrees of freedom (df), “$\overline{x}$” represents the mean cover crop N efficiency expressed as a percent, “se” reflects the standard error, “sd” represents the standard deviation, and “Mann-Whitney” represents the Mann-Whitney Rank Sum Test p-value (p) for t-test comparisons that failed the Shapiro-Wilk test (p<0.05) normality test, “LQ” means the 25th percentile, “Mdn” is the median or the 50th percentile, and “UQ” represents the 75th percentile.

				t-test						**Mann-Whitney**			
App	**Variable**	**Interpretation**	**n**	**p**	**t**	**df**	**$\overline{x}$**	**se**	**sd**	**p**	**LQ**	**Mdn**	**UQ**
	A comparison of legumes and non-legumes												
E	Non-leg.	Non-leg. (E) > Legume (E)	369	< 0.0001	5.7	522	51	1.5	28	< 0.001	28	50	77
E	Legume (leg.)		155				35	2.4	30		8	24	63
	A comparison of non-legume cover crop plant species												
E	Annual ryegrass (A. rye)	A. rye (E) = C. rye (E)	24	0.212	1.3	224	52	4.8	24	0.14	31	54	65
E	Barley	Barley (E) > C. rye (E)	38	< 0.001	6	64	69	3.5	22	< 0.001	51	75	90
		Barley (E) > Barley (M)		0.1	1.7	76				0.08			
E	Cereal rye (C. rye)		202				44	2.0	29		20	39	69
E	Wheat	Wheat (E) > C. rye (E)	48	0.002	-3.1	248	59	4.1	28	0.002	41	61	86
		Wheat (E) > Wheat (M)		0.004	2.9	103				0.004			
M	Barley		40				61	3.3	21		42	64	80
M	C. rye	C. rye (M) > C. rye (E)	50	< 0.001	-7.4	102	71	2.9	21	< 0.001	58	75	88
M	Wheat		57				44	3.3	25		25	43	58

Table K7. ANCOVA equal slopes test and Holm-Sidak comparisons of the difference of adjusted means. Abbreviations: “a” represents the y-intercept, “b” represents the slope, “Adj. x” represents the adjusted mean, “se” represents the standard error, “95%CI” represents the lower and upper confidence interval, “t” represents the t statistic, “p” represents the p-value.

Figure	ANCOVA Group	a	b	Adj. $\bar{x}$	se	p
6a	Previous spring fertilizer N	-2945	1.5	31.8	2.1	< 0.001
6b	Previous fall soil residual	-2923	1.5	53.3	1.6	
9a	Model N efficiencies over growing days	32.7	0.17	62.8	2.2	< 0.001
9b	Empirical N efficiencies over growing days	15.4	0.17	45.5	1.2	
10b	Spring above-ground biomass	-32.6	0.38	32.7	3.1	0.017
10c	Spring above-ground biomass includes cover crops grown on Fall soil residual N with added 80 kg N	-17.3	0.38	48	4.6	
11b	Model groundwater	1.88	0.40	66.9	1.9	< 0.001
11c	Empirical groundwater	-34.7	0.40	30.3	5.5	
12a	Empirical immobilization	-2.3	0.24	34.6	6.5	< 0.001
12b	Model CT soil N	36.2	0.24	73.1	4.7	
13b	Spring above ground with added 80 kg soil N normalized by previous fall soil residual N with added 80 kg N	-0.22	0.24	44	5.3	0.021
13c	Spring above-ground (cereal rye) normalized by previous spring fertilizer N	-13.8	0.24	30	2.3	

Glossary

The following terms are adapted from the Chesapeake Bay Program Quick Reference Guide (CBP 2020c). Terms are further defined in the Chesapeake Assessment Scenario tool (CAST) and directly available in the CAST Source Data Excel sheet at http://cast.chesapeakebay.net/.

Term	Definition
Agricultural conservation plan	An agricultural conservation plan identifies agronomic, management, and engineering practices that prevent the deterioration of natural resources and protect and improve soil productivity and water quality on all or part of a farm.
Agricultural land retirement BMP	A best management practice (BMP) that removes marginal and highly erosive cropland from production by planting permanent vegetation such as shrubs, grasses, or trees.
Alternative crops BMP	A best management practice that grows and manages permanent unfertilized vegetation, such as warm-season grasses, to sequester.
Animal waste management (Animal BMP)	Animal waste management of livestock and poultry includes any structure designed for collecting, transferring, and storing manures and associated wastes generated from the confined portion of animal operations. It complies with NRCS 313 (Waste Storage Facility) or NRCS 359 (Waste Treatment Lagoon) practice standards.
Annual BMP	Best management practices (BMPs) that must be installed every year.
Average load	The loading rate for each land use averaged across the Chesapeake Bay watershed. Average loads are not true edge-of-field loads, but rather the average load that would reach a small stream.
BMP action scenario	To calculate the nutrient best management practice (BMP) action scenario, multiply progress year post-BMP area by the Progress year nutrient loading rate for the edge-of-stream. A progress year post-BMP area is the area of load sources in the land-river segment after land use change BMPs are credited.
Barnyard runoff control BMP	Best management practices (BMPs) that include roof runoff control, diversion of clean water from entering the barnyard, and control of runoff from barnyard areas.
Commodity cover crops BMP	Commodity cover crops are best management practices (BMPs) similar to traditional cover crops, except that farmers can harvest commodity cover crops in the spring.

Term	Definition
Conservation tillage BMP	Conservation tillage best management practices (BMPs) require a minimum of 30% residue coverage at the time of planting and a non-inversion tillage method.
Continuous high tillage BMP	Continuous high tillage best management practices (BMPs) achieve a minimum of 60% crop residue cover on the soil surface immediately after planting by minimizing soil disturbance via plows and inverting crop residue on multi-crop, multi-year rotations.
Conventional denitrification	Employ a 50% denitrification pre-treatment waste unit with no enhanced in situ treatment system within the soil treatment unit.
Credited BMPs	In a CAST progress scenario, credited BMPs indicate enough units of load sources within the land river segment have been reported for the BMP implementation.
Edge of Stream Load, nutrients	Edge-of-stream loads represent the nutrient load export from a land use to a stream or waterbody in a land-river segment due to local applications but not local watershed conditions. The edge-of-stream loads are reported for nutrients and incorporate the average load, inputs, and sensitivities.
Edge of Stream Load, sediments	For sediments, edge-of-field loads are reported and include the average load and do not include inputs and sensitivities. Sediment loads are determined by the RUSLE model and further explained in detail in the Phase 6 watershed Model section 2 Average Loads. Nutrient and sediment loads are then multiplied by the area of the land use in the segment (Land Use Acres) and the effect of local best management practices.
Efficiency values	Percentage of pollutants reduced by implementing a best management practice.
Erosion and sediment control (Rural-urban development BM)P	Traps or remove sediment and rapid vegetative cover for stabilization.
Exclusionary fencing in grass and forest buffers	This agricultural best management practice (BMP) converts streamside pasture to open space or forest to prevent livestock from entering the stream.
Forest buffers (Agricultural BMP)	Linear wooded areas help filter sediments and remove nutrients and other pollutants from runoff and groundwater originating from agricultural land uses.
Forest buffers (Rural-urban development BMP)	Linear wooded areas help filter nutrients and other pollutants from runoff and groundwater.
Forest harvesting practices (Natural BMPs)	Reduce suspended sediments and associated nutrients from logging operations by minimizing the environmental impacts of road building, log removal, site preparation, and forest management.
Functional BMPs	Operating best management practices assumed to remove nutrients per design.
Grass buffers (Agricultural BMP)	This best management practice (BMP) includes linear strips of grass or other non-woody vegetation maintained to help filter nutrients, sediment, and other pollutants from runoff.

Term	Definition
Horse Pasture Management (Agricultural BMP)	This best management practice (BMP) maintains a 50% pasture cover with managed species (desirable, inherent) and managed high-traffic areas.
Infiltration and filtering practices (Rural-urban development BMP)	Infiltration best management practices (BMPs) are depressions that trap sediment and allow for water infiltration while filtering practices are strips of stable, vegetated cover on flat or gently sloping land.
In-situ soil treatment of septic effluent	The septic system is designed to reduce total nitrogen by 38% (Enhanced) or 50% (Advanced) by employing an in-situ soil treatment system with no secondary treatment or enhanced denitrification technology.
Land-river segment	The intersection of a land segment (portions of counties) and a river segment (uninterrupted waterway lengths).
Load source	Varying land uses in agriculture, development, natural, septic, and animal sectors are characterized by nutrient by areal rate in kg^{-1} ha y^{-1}.
Load source change	The land use change from a higher nutrient load (livestock pasture) to a lower nutrient load (forest).
Load source with efficiency values	Best management practices change a land use to a lower nutrient load and reduce upland area nutrient export.
Loafing lot management (Agricultural BMP)	This best management practice (BMP) includes stabilizing areas frequently and intensively used by people, animals, or vehicles by establishing vegetative cover, surfacing with suitable materials, and/or installing needed structures except for poultry pad installation.
Low-till (Agricultural BMP)	This best management practice (BMP) requires 15-29% cover and less than 40% soil disturbance after tilling. This BMP is also known as strip-till or no-till.
Manure incorporation (Agricultural BMP)	Occurs over 1 to 3 days with low (<40%) soil disturbance or within 24 hours with low to high soil disturbance levels.
Manure injection (Agricultural BMP)	Manure injection is the process of immediately incorporating manure into the soil.
Manure transport (Animal BMP)	Excess animal manure is physically moved out of a county and into another county.
Mortality composter (Animal BMP)	A physical structure and process for disposing of any dead animal that is eventually land applied according to nutrient management plan recommendations.
Multi-annual BMP	Typically, a structural best management practice (BMP) that is designed to have an operating life-span of more than one consecutive year
Mutually exclusive BMPs	Best management practices (BMP) that cannot physically occupy the same land area. These are additive, so their efficiencies can be added together.
No BMP edge-of-stream action scenario	To calculate a No best management practice (BMP) action scenario for total nitrogen, total phosphorus, or total suspended solids, multiply progress year pre-BMP area and the 2010 No Action nutrient loading rate for edge-of-stream. A Progress year pre-BMP area does not consider land use change BMPs.

Term	Definition
Non-urban stream restoration (Natural BMPs)	Improves the stream corridor habitat and water quality conditions in degraded streams to restore the natural hydrology and landscape of the stream ecosystem.
Nutrient management practices (Agricultural BMP)	Nutrient management practices address the placement, rate, and timing of the core N and P BMPs. The nutrient management core N BMP includes five elements: 1) application rate modification; 2) manure analysis used in the plan; 3) calibrated spreader within one year; 4) yield estimates used in the plan; 5) legume residual N credits and manure mineralization are credited as part of the plan. The nutrient management core P BMP includes six elements: 1) application rate modification; 2) P soil test used in the plan; 3) manure analysis used in the plan; 4) calibrated spreader within one year; 5) yield estimates used in the plan; 6) legume residual N credits and manure mineralization are credited as part of the plan.
Off-stream watering without fencing (Agricultural BMP)	This best management practice (BMP) uses alternative drinking water sources, such as permanent or portable livestock water troughs, placed away from the stream corridor.
Overlapping or multiplicative BMPs	Best management practices (BMPs) that can be applied to the same land area.
Pass-through value	The amount of nutrients not removed by the best management practice.
Pasture	Land used for pasture or grazing animals. Fertilizer and manure may be applied in addition to directly excreted manure.
Poultry litter amendments (Animal BMP)	Poultry litter amendments, such as alum, reduce ammonia volatilization to minimize hazardous ammonia emissions from poultry houses.
Precision intensive rotational/prescribed grazing (Agricultural BMP)	Management practices for precision intensive rotational/prescribed grazing reduce the impact of animal travel lanes, animal concentration areas, or other degraded areas, and vegetative cover must be greater than 60% of the pasture.
Progress year	Scenario reports reflect the BMPs that are functioning in the July1 to June 30 year, the year's land use and land cover base conditions, and assumes maximum feasible air reductions.
Riparian fencing (Animal BMP)	Prevents livestock from grazing in riparian areas.
Rural-urban Nutrient Management Plan	A rural-urban nutrient management plan (NMP) is a written, site-specific document that outlines how to manage nitrogen, phosphorus, and potassium for expected turf and landscape plants with the aim of water quality protection.
Septic connection	Removes wastewater from onsite private septic tanks and transfers the wastewater to public sewer systems, where treatment and nutrient load reduction occur.
Septic pumping	This BMP recommends pumping septic tanks once every three to five years to maintain effectiveness. Solids are removed from the septic tank to prevent clogging and the overall failure of the system. A failed system poorly filters and treats effluent, which can enter ground and surface water sources.
Stormwater practices (Rural-urban development BMP)	Include various stormwater management BMPs, including stormwater performance standard practices that achieve at least a 25% reduction of

Term	Definition
	annual surface runoff volume post-development, and depression basins, such as bioretentions, rain gardens, and bioswales that aim to intercept, filter, and infiltrate stormwater.
Street sweeping (Rural-urban development BMP)	Street sweeping occurs regularly during the spring and summer to remove debris from the streets.
Traditional cover crops (Agricultural BMP)	Short-term crops are sown after the primary cropping season to sequester unused nutrients during the winter. Fall nutrients are not applied, and a spring harvest is not permitted.
Tree planting (Agricultural BMP)	Occurs outside of riparian forest buffers and target lands that are highly erodible or identified as critical resource areas.
Tree planting (Rural-urban development BMP)	The goal of tree plantings is to increase tree canopy in developed areas.
Water control structure (Agricultural BMP)	The installation and management of boarded gate systems in agricultural land that contains surface drainage ditches.
Wetland creation (Agricultural BMP)	Establishes wetlands where one did not previously exist.
Wetland rehabilitation (Natural BMPs)	Improves the overall function of degraded wetlands by manipulating the physical, chemical, or biological characteristics.
Wetland restoration and rehabilitation (Agricultural BMP)	Re-establish a wetlands' natural/historic functions by manipulating the physical, chemical, or biological characteristics.
Wetlands, wet/dry ponds, dry detention ponds (Rural-urban development BMP)	Wetlands and wet ponds retain a permanent pool of water, while dry ponds typically dry out between storm events, and all function to intercept stormwater runoff.

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