ABSTRACT

Title of dissertation:	NOVEL APPLICATIONS IN WETLAND SOILS MAPPING ON THE DELMARVA COASTAL PLAIN
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On the Delmarva Peninsula, depressional wetlands provide a range of ecosystem services, including water purification, groundwater recharge, provision of critical habitat, and carbon storage. Concern for the health of the Chesapeake Bay and the establishment of the Bay Total Maximum Daily Load have led to growing interest in restoring depressional and other wetland types to mitigate agricultural nitrogen inputs. The ability of natural resource managers to implement wetland restoration to address nonpoint source pollution is constrained by limited spatial information on hydrogeologic and soil conditions favoring nitrogen removal. The goal of this study was to explore the potential of new digital soil mapping techniques to improve identification of wetland soils and map soil properties to improve assessment of wetland ecosystem services, including removing excess nitrogen, and inform natural resource decision making. Previous research on digital soil mapping has focused largely on the development of medium to low-resolution

general purpose soil maps in areas of heterogeneous topography and geomorphology. This study was unique in its focus on mapping wetland soils to support wetland restoration decisions in a low relief landscape. A digital soil mapping approach involving the spatial disaggregation of soil data map units was used to create maps of natural soil drainage and texture class. The study was conducted in the upper part of the Choptank River Watershed on central Delmarva, where depressional wetlands occur in high densities and historical loss of wetlands is estimated to be high compared to similar Maryland watersheds. The soil disaggregation techniques developed in this study were successful in creating a more refined representation of natural soil drainage and texture class in forested depressional wetlands. Comparison of the disaggregated soils map with recently developed time-series inundation maps of the region demonstrate the need for further research to understand how indicators of historic and current hydrologic conditions can guide operational soils and wetland mapping and inform wetland restoration decisions.

NOVEL APPLICATIONS IN WETLAND SOILS MAPPING ON THE
DELMARVA COASTAL PLAIN

by

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Dedication

This dissertation is dedicated to my parents, Tom and Cindy Goldman.

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Chapter 1 – Introduction

1.1 Wetlands and water quality

Wetlands are often highly productive ecosystems found in nearly all parts of the world. They are characterized by water saturation at or near the surface or inundation for varying periods of time throughout the year, including during the growing season. The frequency and duration of saturation or inundation is sufficient to support the development of unique soil conditions and vegetation that is adapted to saturated soils. There are many different kinds of wetlands, including marine and coastal wetlands such as tidal marshes, estuaries, and freshwater lagoons; and inland wetlands such as prairie potholes, playa lakes, and bogs. Due largely to their hydrology, wetlands provide valuable functions that provide many benefits to society, such as flood storage, shoreline stabilization, fish and wildlife habitat, carbon storage, and water purification.

Hydrologic conditions determine the physicochemical environment in wetlands that support specific biota, which in turn modify the physicochemistry and hydrology of wetlands (Mitsch and Gosselink, 2007). The dynamic relationships that arise from the interaction of hydrologic, physicochemical, and biotic factors within different geomorphic settings determine the functions of a wetland. Water purification is among the most widely recognized and highly valued functions that wetlands provide. Wetlands purify water by dissipating stream energy and filtering and transforming nutrients and other contaminants transported by surface and groundwater.

Since European settlement, the conterminous U.S. has lost over half of its wetlands (Dahl, 1990). In the Chesapeake Bay watershed, which expands more than 64,000 square miles across six states, development, agriculture, invasive species, and sea level rise threaten tidal and non-tidal wetland habitats. Wetlands are vital in supporting clean water in the Chesapeake Bay watershed. Concern for the health of the Chesapeake Bay and the establishment of the Bay Total Maximum Daily Load (TMDL), a 'pollution diet' to restore clean water in the Chesapeake Bay and its tidal tributaries, have led to growing interest in restoring wetlands to mitigate pollution. Excess nitrogen and phosphorus in the Bay promote the growth of harmful algal blooms that block sunlight from reaching submerged aquatic vegetation and reduce or eliminate oxygen in the water column, creating 'dead' zones' where fish and other animals cannot survive. In recent decades, the ecological and economic health of the Chesapeake Bay has deteriorated due to pollution from excess nutrients and sediment. As a result, the Chesapeake Bay and many of its tidal waters have been designated as "impaired waters" under section 303(d) of the federal Clean Water Act. The Chesapeake Bay TMDL sets pollution limits on nitrogen, phosphorus, and sediment necessary to meet water quality standards set by the U.S. Environmental Protection Agency (USEPA) in the Bay and its tidal rivers.

The Delmarva Peninsula contributes disproportionately large loads of excess nitrogen and phosphorus to the Chesapeake Bay, most of which is sourced from agriculture (Ator and Denver, 2015). Nitrogen moves primarily from source areas on the landscape to tidal waters as nitrate in groundwater, whereas phosphorus moves from source areas to tidal waters primarily in particulate form over the land surface (Ator and Denver, 2015). Wetlands can function as removal sites for nitrogen primarily by promoting

denitrification, an anaerobic process in which microbes convert nitrate to gaseous nitrogen products, thereby permanently removing nitrogen from the soil-water environment. Wetlands can be highly efficient at removing nitrate, and if located at critical points in the landscape, have potential to provide significant water quality benefits at the watershed scale (Hansen et al., 2018). The 2014 Chesapeake Bay Watershed Agreement includes the outcome of creating or reestablishing 34,400 hectares of tidal and nontidal wetlands and enhancing the function of an additional 60,700 hectares of degraded wetlands by 2025 (Chesapeake Bay Program, 2014).

Seventy percent of the total nitrogen load from headwater streams on the Delmarva is transported to the Chesapeake Bay as nitrate in groundwater (Ator and Denver, 2015). Denitrification is observed in a variety of settings on the Delmarva, including depressional and riverine wetlands (Denver et al., 2014; Jordan et al., 2007), riparian floodplains (Duff et al., 2008; Puckett, 2004), along groundwater flowpaths (Bohlke and Denver, 1995; Denver et al., 2010), and in coastal swamps and marshes (Speiran, 1996). Complex interactions between land cover, soils, and geomorphology affect the fate and transport of nitrate from source areas to streams (Ator and Denver, 2015; Hamilton et al., 1993; McCarty et al., 2008). An understanding of the conditions favoring denitrification in wetlands across the landscape is therefore necessary to plan wetland restorations at the watershed scale to improve water quality.

1.2 Choptank River Watershed

The 1756 km^2 Choptank River Watershed on the central Delmarva is relatively flat, with a maximum elevation of less than 30 m (Lee et al., 2000). Land cover in the Choptank Watershed is dominated by agriculture (65%), with smaller amounts of forest (26%) and urban areas (6%) (Fisher et al., 2006). Historical loss of wetlands in the upper part of the Choptank Watershed is estimated to be 19,200 ha; approximately 11% of the entire watershed area (MD DNR, 2002).

The Choptank River Watershed is the focus of several long-term watershed studies, including the U.S. Department of Agriculture Conservation Effects and Assessment Project (CEAP). Objectives of CEAP include developing innovative remote sensing tools for monitoring wetland hydrology and connectivity on a watershed scale, examining the effects of land use and hydrology on nutrient and pesticide loading to streams, and developing watershed-scale water quality models to evaluate the effectiveness of conservation practices in the watershed. Water quality sampling throughout the watershed, much of which has recently been supported by CEAP, provides a rich dataset on hydrologic and geochemical conditions in the Choptank dating back to 1964 (Fisher et al., 2006; McCarty et al., 2008). The availability of these data makes the Choptank Watershed an excellent study area for testing new remote sensing and modeling techniques.

1.3 Depressional wetlands

Depressional wetlands, known locally as Delmarva bays, occur in high densities throughout the northern part of the Choptank River watershed. Delmarva bays are similar to Carolina bays, which are found on the Atlantic Coastal Plain from Florida to New Jersey. Carolina bays are shallow, elliptical depressions with well-defined sandy rims (Prouty, 1952; Stolt and Rabenhorst, 1987a; Thom, 1970). They are often oriented northwest to southeast along the major axis and the sandy rims are usually best developed on the southeast side (Prouty, 1952; Sharitz and Gibbons, 1982). Carolina bays range from less than a hectare to greater than 3,600 hectares in size, and are most abundant in southeastern North Carolina and mid-coastal South Carolina (Sharitz, 2003). Delmarva bays are typically much smaller and less elliptical than Carolina bays, but are believed to have formed from similar processes during the late Pleistocene (Fenstermacher et al., 2014; Stolt and Rabenhorst, 1987a). The most accepted theory of the formation of Delmarva and Carolina bays is that they are the product of blowouts; the depressions were created when strong winds removed sandy soil material, resulting in areas where the water table was above the surface. The characteristic elliptical shape and sandy rims were formed by wind-driven currents in the ponded water (Prouty, 1952; Savage, H., 1982; Stolt and Rabenhorst, 1987a).

Many Delmarva bays contain a silty basin fill which is absent from most Carolina bays to the south (Stolt and Rabenhorst, 1987a). Depressions that have a silty basin fill typically have steeper slopes and greater relief than those with a sandy bottom (Stolt and Rabenhorst, 1987a). The silty basin fill in low areas of the depressions likely originated

from loess that was deposited during the last glacial period and gradually eroded to the center of depressions (Stolt and Rabenhorst, 1987a).

Delmarva bays exhibit a range of hydroperiods – from frequently dry to semipermanently flooded (De Steven and Lowrance, 2011). Water levels fluctuate seasonally and interannually and are strongly influenced by recent precipitation and the local groundwater flow system (Phillips and Shedlock, 1993). Water levels drop in the summer with increases in temperature and evapotranspiration. Delmarva Bays can act as both a recharge wetland in the summer and a discharge wetland in winter and spring (Phillips and Shedlock, 1993).

Many depressional wetlands have been lost through artificial drainage and conversion to agriculture (De Steven and Lowrance, 2011), but complexes of depressional wetlands remain in poorly drained forested areas throughout the upper Choptank River watershed. Depressional wetlands are among the most challenging wetlands to map and monitor due to their variable hydroperiod, small size and low relief (Lang et al., 2013; Tiner, 1990). They are particularly difficult to map when forested, and most bays are naturally forested. Regardless, wetland mapping and monitoring is essential for informed natural resource management and policymaking (Lang and McCarty, 2008).

1.4 Forested wetland mapping

Traditionally, wetland mapping has relied on aerial photographs, but with increasing availability of fine-resolution optical data, radar, and lidar data, and advances in geospatial modeling, there is great potential to improve wetland maps and monitoring

efforts (Lang and McCarty, 2008). Several studies have been conducted through CEAP to advance the use of remote sensing in mapping and monitoring wetlands. In the Choptank Watershed, lidar-derived DEMs have been used to develop topographic metrics to predict forested wetland location (Lang et al., 2013) and to enhance detection of wetland-stream connectivity (Lang et al., 2012). Lidar systems are active sensors that emit short pulses of energy in the infrared part of the spectrum, calculating the distance to an object by recording the amount of time it takes for a pulse to return to the sensor. Lidar can be used to calculate highly accurate x, y, z locations. Whereas conventional digital elevation models (DEMs) have vertical accuracies of 1-10 m, lidar DEMs have vertical accuracies of 15 cm – 1 m) (Lang and McCarty, 2008).

Lidar intensity (a measure of the strength of the return signal) can be used to detect wetland inundation. In the Choptank watershed, lidar intensity data were used to map inundation in forested wetlands with greater than 96% accuracy (Lang and McCarty, 2009). A novel approach combining lidar intensity and Landsat time-series imagery has been developed in the region to map wetland inundation change over time (Huang et al., 2014; Jin et al., 2017). Accuracy assessments of the inundation maps indicate that they can be used to extract long-term information on inundation dynamics with relatively low degrees of uncertainty (Jin et al., 2017).

1.5 Soils mapping

The U.S. Soil Survey Geographic Database (SSURGO) provides a major data source for support of identification and monitoring of natural, restored, and former depressional

wetlands and estimation of wetland ecosystem services. Soils data can be used to predict where wetlands occur or once occurred. Natural soil drainage class represents the frequency and degree of saturation under which a soil formed, which can be important for evaluating changes in hydrology and function due to anthropogenic factors. Soil maps can be used in modeling wetland ecosystem services at regional (Ator and Denver, 2012) and watershed (Tomer et al., 2013) scales and identifying potential restoration sites (Hunter et al., 2012).

Efforts to utilize SSURGO soils data in water quality models and land management planning on the Delmarva are hampered by the coarse scale of survey maps relative to the scale of restoration decisions, the spatial aggregation of soil components, and the difficulty in accounting for uncertainty in soil maps. The subtle variations in topography depicted by fine-resolution lidar data are often not reflected within conventional soil maps. Extensive ditch drainage in agricultural and forested areas of the poorly drained portions of the Choptank watershed further limits the use of soils data in mapping current hydrologic conditions. New digital soil mapping techniques, including spatial disaggregation of soil data map units, have great potential to improve our ability to identify wetland soils and map soil properties to improve assessment of wetland functions and conservation practices and predict the effects of land management decisions on water resources. Spatial disaggregation is "the process of separating an entity into component parts based on implicit spatial relationships or patterns" (Moore, 2008). In general, disaggregation methods aim to create a more refined representation of soil classes and properties by identifying components within map units to meet new demands for soils data (D'Avello and Nauman, 2013).

1.6 Dissertation overview

This dissertation is composed of three principal chapters. Chapter 2 presents an examination of the challenges to developing a watershed-scale approach to wetland restoration and creation for nitrate removal in the Chesapeake Bay watershed. This chapter also serves as the primary literature review for the dissertation. Biological/physical and political/social/economic challenges are explored through a review of the relevant literature and discussion of potential avenues of research for addressing the identified challenges. One of the major challenges identified in Chapter 2 is accounting for subsurface connectivity between nitrogen sources and wetlands. Subsurface connectivity is dependent on local hydrogeologic and soil conditions. A proposed approach for addressing this challenge is improved use of geospatial data for predicting subsurface connectivity, including: 1) expanded use of lidar data and topographic indices derived from lidar; 2) better use of soils data; 3) incorporation of ditch network data; and 4) incorporation of remote-and ground-based sensor techniques for measuring variability in soil and vegetation characteristics. Chapter 2 introduces soil survey disaggregation as a possible way to improve the use of soils data to better identify areas where hydrology and soil conditions may favor N removal by wetlands.

Chapter 3 presents a methodology for disaggregating soil survey map units for the purpose of supporting wetland restoration and conservation decisions in low-relief depressional wetland landscapes on forest and cropland. This is the main component of my dissertation research. Field data compiled from previous research and the local soil survey were used to train separate disaggregation models for forest and cropland using the Random Forests machine learning algorithm. Topographic metrics derived from lidar,

SSURGO, the National Wetlands Inventory, and ditch network data are used as covariates to predict natural soil drainage class and texture class. In forested areas, model predictions fit the tacit understanding of variability in natural soil drainage class and texture class on depressional wetland landforms. One of the limitations of the forest model, however, was that it was not able to differentiate very poorly from poorly drained soils. Chapter 4 addresses this limitation.

Chapter 4 is an exploratory data analysis comparing the disaggregated soils map with time-series inundation maps of the region developed from Landsat and lidar intensity data (Huang et al., 2014; Jin et al., 2017) to determine whether the inundation data may help distinguish soils that are likely very poorly vs poorly drained in the study area. Chapter 4 includes 4 objectives:

1) Compare the disaggregated soil drainage class map with the inundation maps;
2) Identify zones within areas mapped as very poorly drained/poorly drained that show stable, variable, or consistently low inundation patterns;
3) Compare the topographic metrics with the inundation data; and
4) Suggest potential avenues of research for investigating uses of the inundation data in wetland soils mapping.

Implications for wetland soils and wetland extent mapping to support the assessment of wetland functions (e.g., nitrate removal) at a landscape scale and enhance the implementation of wetland conservation and restoration practices are discussed.

Chapter 2 – Wetland Restoration and Creation for Nitrogen Removal: Challenges to Developing a Watershed-Scale Approach in the Chesapeake Bay Coastal Plain

2.1 Introduction

Nitrogen losses due to increases in agricultural applications of fertilizer and manure over the past 60 years have contributed to eutrophication, hypoxia, and habitat loss in the Chesapeake Bay. The Chesapeake Bay receives an estimated 1.32 108 kg N per year, with agriculture contributing more than half of this load (Ator et al., 2011). In 2010, the US Environmental Protection Agency established the Chesapeake Bay Total Maximum Daily Load (TMDL), a "pollution diet" for the Chesapeake Bay and the region's creeks, streams, and rivers. The TMDL sets pollution limits on nitrogen, phosphorus, and sediment necessary to meet water quality standards in the Bay and its tidal rivers. For nitrogen, this limit is set at 84.3 million kg N per year. Measures to achieve the TMDL must be in place by 2025 with 60% completion by 2017 (U.S. Environmental Protection Agency, 2010). Bay states are required to develop watershed implementation plans (WIPs) that document how local jurisdictions will work with state and federal governments to control nutrient and sediment loads and meet TMDLs. WIPs are to be

submitted to the EPA in three phases with increasing level of detail: Phase I implementation plans in November 2010, Phase II in March 2012, and Phase III in 2017.

Reducing nutrient loading from agricultural sources will require a broad suite of practices, including on-farm, edge-of-field, and off-site practices. One potential edge-of-field or off-site strategy is targeted restoration and creation of wetlands. Wetlands can function as removal sites or "sinks" for N primarily by promoting denitrification, a microbial process by which nitrate is converted to gaseous nitrogen products thereby permanently removing N from the soil-water environment. The 2014 Chesapeake Watershed Agreement includes the outcome of creating or reestablishing 34,400 hectares of tidal and nontidal wetlands and enhancing the function of an additional 60,700 hectares of degraded wetlands by 2025 (Chesapeake Bay Program, 2014).

The restoration and creation of wetlands for controlling nonpoint source pollution in agricultural watersheds has been widely investigated (Hernandez and Mitsch, 2007; Jordan et al., 2003; Kovacic et al., 2000; Phipps and Crumpton, 1994; Poe et al., 2003; Vellidis et al., 2003). For over 20 years, research in this area has emphasized the need for a watershed-scale approach to siting and designing wetlands in order to optimize performance and meet water quality goals (Crumpton, 2001; De Steven and Lowrance, 2011; Mitsch et al., 2001; Osmond et al., 2012; Passeport et al., 2013; Van der Valk and Jolly, 1992; Woltemade, 2000; Zedler, 2003). In addition to biological and physical constraints, wetland restoration planning requires consideration of political, economic, and social factors that may pose barriers to implementation and are best addressed at the watershed scale. Wetland restoration must also be considered within the context of the broader response strategy, as one of many potential ways to address agricultural nonpoint

source pollution. Van der Valk and Jolly (1992) outlined a set of recommendations for research on the use of wetlands to address nonpoint source pollution:

- Whole watershed demonstration studies

- Studies of effectiveness of restored/created wetlands

- Landscape simulation models of origin/movement of nonpoint source pollution

- Studies on site selection and design criteria

- Studies of farmers' and local business/community leaders' attitudes toward landscape approach

- Studies exploring legal and public policy issues of wetland restoration programs

- Studies evaluating the costs and benefits of this approach

There has been little advancement in these research areas in the Chesapeake Bay watershed to date. Wetland projects are still planned primarily at the scale of the individual property. However, in recent years, environ- mental groups have initiated pilot projects in parts of the watershed to demonstrate the application of a watershed approach to wetland and stream restoration, with applications in both conservation planning and compensatory mitigation (The Nature Conservancy, 2013; Wilkinson et al., 2013).

This paper addresses some of the barriers to implementing wetland restoration/creation practices in the region, discusses challenges to developing a watershed approach for treating nitrate, and recommends ways to overcome these challenges. We focus on the coastal plain portion of the Chesapeake Bay watershed because of the great potential for wetland restoration in this region due to the widespread agricultural land use and history of artificial drainage of wetlands.

2.2 Biological and Physical Challenges

In taking a watershed-scale approach to siting and designing wetlands for mitigating nitrate runoff, we should consider where on the landscape agricultural nitrate is being delivered to streams and where the topography and soils are most suitable for wetland establishment. Where these factors coincide, there is an opportunity to restore or create wetlands that will be effective at removing nitrate and improving water quality. We have identified two major biological and physical challenges for the siting of wetlands for nitrate removal: (1) accounting for subsurface connectivity between nitrogen sources and wetlands and (2) estimating how effective wetlands will be at removing nitrate in order to demonstrate the benefits of targeted wetland restoration and compare alternative watershed plans.

2.2.1 Subsurface Connectivity between Nitrogen Sources and Wetlands

A wetland can only be effective at mitigating N if there is hydrologic connectivity between the N source and the wetland site. Nitrogen transport in the coastal plain of the Chesapeake Bay watershed is often subsurface and varies in depth and transport time. Also, the direction of flow does not necessarily follow topographic patterns. Subsurface hydrologic connectivity is not consistent over time and may be altered through hydrologic restoration.

The Delmarva Peninsula forms the largest portion of the Mid-Atlantic Coastal Plain portion of the Chesapeake Bay watershed. The flat topography and permeable soils of much of the Delmarva Peninsula favor subsurface flow (Hamilton et al., 1993; Staver and

Brinsfield, 1998). Nitrate leaching from the crop rooting zone during winter months contributes to elevated groundwater nitrate concentrations (Staver and Brinsfield, 1998). The peninsula is underlain by a wedge of unconsolidated sediments comprised of a surficial unconfined aquifer ranging from less than 6 m to greater than 30 m thick (Hamilton et al., 1993) underlain by a series of confined aquifers (Cushing et al., 1973) (Fig. 2.1). Due to the high permeability of aquifer sediments, groundwater is well oxygenated throughout most of the aquifer and elevated nitrate concentrations are found even near the base of the surficial aquifer (Debrewer et al., 2007; Hamilton et al., 1993). Seventy percent of the nitrogen flux in headwater streams is attributable to base-flow nitrate flux (Ator et al., 2013). Debrewer et al. (2007) reported that median nitrate concentrations in groundwater are greater than 5 mg L^{-1} and often higher than 10 mg L^{-1} in wells placed at a median depth of 6 m below the surface in agricultural areas. Similar nitrate concentrations in deeper groundwater (14 m below surface) reflect recharge in upgradient agricultural land (Debrewer et al., 2007; Hamilton et al., 1993). Mitigating nitrate loss is further complicated by the long travel time required for deep groundwater to move through the surficial aquifer; nitrate may remain in groundwater for decades to centuries before discharging into streams (Bohlke and Denver, 1995).
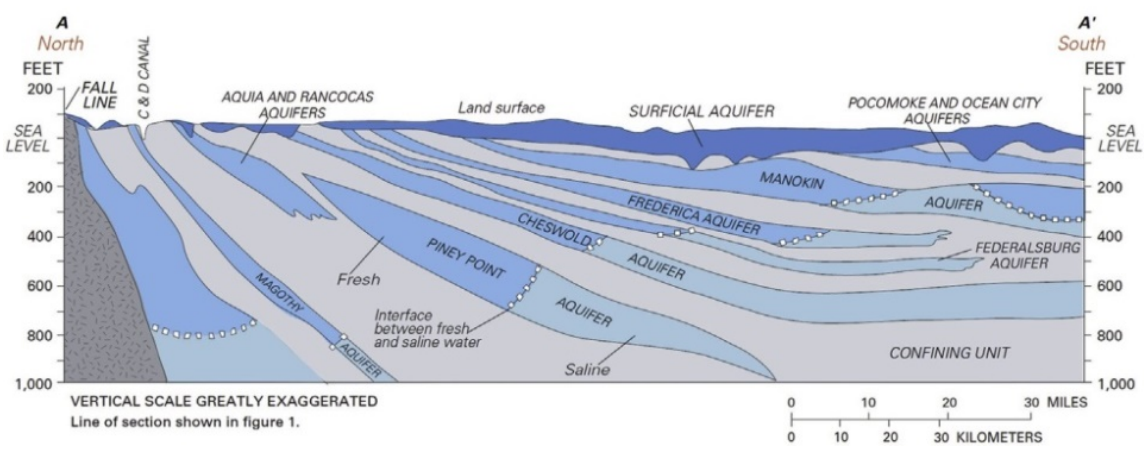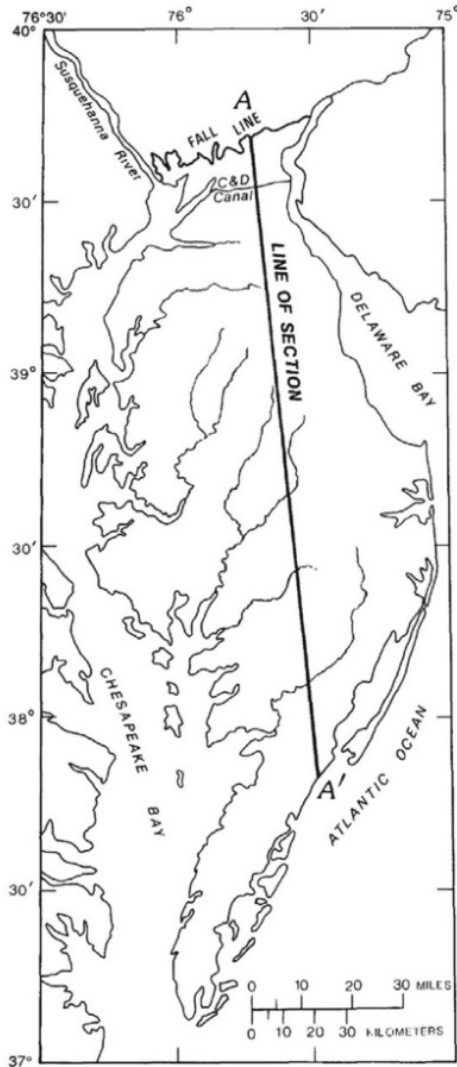
Figure 2.1 Stratigraphies of the Delmarva Peninsula. An extensive surficial aquifer overlies a series of confined aquifers. *Image produced by the US Geological Survey, Hamilton et al. (1991) with modification by Denver et al. (2004).*

Depressional wetlands have been the focus of much of the wetland restoration efforts on the Delmarva Peninsula. Two common wetland restoration techniques are commonly used in these landforms: (1) plugging agricultural drainage ditches and (2) excavating the topsoil and building a berm ("scraping"). In some cases, ditch-plugging may not be effective for groundwater nitrate mitigation. When a ditch is plugged, the water level in the ditch rises reducing the hydraulic gradient between the ditch and the groundwater. Groundwater that previously flowed into the ditch may begin to flow in another direction, potentially bypassing the wetland treatment area (T. Jordan, 2013, pers. comm.). Scraping is a more common practice in Maryland, but it is also unclear how this method affects N transport and processing. By compacting the subsoil during excavation, scraping likely affects soil properties such as bulk density and pore size distribution, with important implications for the fate of subsurface N.

Potential restoration sites are evaluated through site visits and examination of topographic and soils maps, but these methods often do not adequately account for subsurface hydrologic flow paths, which are a major transport pathway of nitrate in coastal plain regions of the Chesapeake Bay watershed (Hamilton et al., 1993; Sanford et al., 2012; Staver and Brinsfield, 1996).

Tile and ditch drainage are common in poorly drained agricultural areas, where wetlands are most likely to be successfully established. Artificial drainage networks can provide a conduit for the rapid and continuous de- livery of nitrate to surface waters. Few studies have been published on the effects of artificial drainage on water quality on the Mid-Atlantic Coastal Plain (Kleinman et al., 2007; Needelman et al., 2007; Schmidt et al., 2007; Vadas et al., 2007), but recent research in Maryland has shown that ditch depth and

the presence of subsoil clay-rich horizons can affect transport of nitrate through ditches (Schmidt et al., 2007; Vadas et al., 2007). Shallow ditches (0.5 m) function mainly as conduits for surface water during runoff-generating rainfall events, receiving few subsurface inputs (Schmidt et al., 2007). Deeper ditches (1 m) drain proportionately more water due to continuous subsurface flow inputs, and nitrate loss increases linearly with drainage outflow (Schmidt et al., 2007). The presence of low conductivity clay-rich horizons can cause water tables to perch temporarily following rain events, promoting rapid, lateral movement of water to ditches (Vadas et al., 2007). Old drainage ditches within restored wetlands can also have important implications for nitrate transport. Vellidis et al. (2003) identified preferential flow paths associated with old drainage ditches that permitted groundwater nitrate plumes to flow deep within wetland soils, limiting interaction with the biologically active rooting zone. Nitrate-enriched groundwater from agricultural fields is generally expected to flow through riparian areas to streams laterally through the shallow subsurface (Gold et al., 2001; Lowrance et al., 1997) (Fig. 2.2). However, subsurface flow may be more heterogeneous and asymmetrical than this general model predicts (Angier et al., 2005; Gold et al., 2001). In some locations, deeper groundwater or preferential flow paths can deliver nitrate directly to streams with limited opportunity for N processing (Angier et al., 2005; Gold et al., 2001) (Fig. 2.2). Thus, in areas where subsurface flow is the primary transport of nitrate, the effectiveness of wetland best management practices (BMPs) to mitigate nitrate depends on our ability to understand how nitrate is moving in the subsurface.
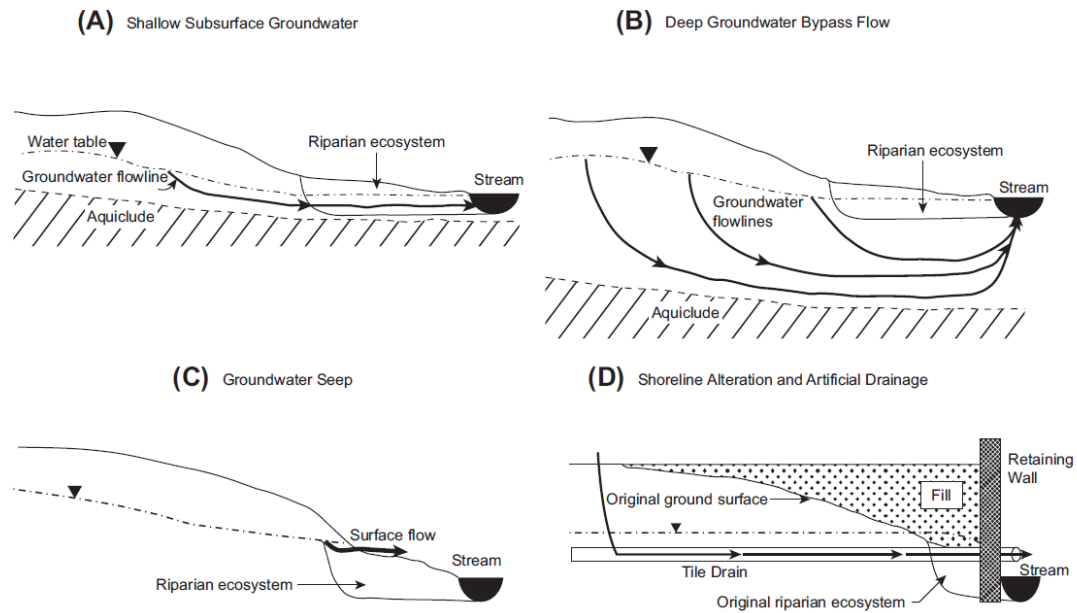
Figure 2.2 Groundwater flow paths through riparian areas can control the delivery of nitrate-enriched groundwater to streams. (A) Substantial interaction of ground water with biologically active zone in shallow aquifers; (B) Direct upwelling to streams in deep aquifers; (C) Bypass flow due to surface seeps; (D) Bypass flow due to filling and artificial drainage. *Reprinted with permission, Gold et al. (2001).*

Subsurface flow may follow preferential flow pathways controlled by variations in soil and aquifer characteristics horizontally and with depth. Both macropore flow and funneled flow have important implications for so- lute transport. Kung (1990) identified preferential flow triggered by funnels created by abrupt textural discontinuities and inclined bedding planes as the dominant mechanism in a sandy vadose zone in Wisconsin. Funneled flow allows for rapid transport of contaminants and can be difficult to detect using common solute sampling techniques (Kung, 1990).

In a first-order riparian zone in an agricultural catchment in the Mid- Atlantic Coastal Plain, Angier et al. (2005) found that much of the groundwater nitrate was delivered to a

stream through zones of concentrated flow. The authors observed higher hydraulic conductivities associated with 5-cm thick sand layers 80 and 120 cm below the surface within otherwise low conductivity fine-textured wetland soils. These layers probably acted as preferential transport sites, delivering groundwater to discharging macropores along the stream (Angier et al., 2005). Upwelling zones supplied a disproportionate amount of total stream flow, including a single upwelling area that comprised 0.006% of the riparian area but generated on average 4% of total stream flow (Angier et al., 2005). This example illustrates the importance of being able to identify surface features and soil properties that control hydrologic connectivity. Traditional models of horizontal matrix flow were inadequate for describing the connectivity of this riparian ecosystem where significant amounts of nitrate reached the stream channel.

Differences in soil and aquifer hydraulic properties and the depth of groundwater flow have important implications for siting and designing wetlands. Where the surficial aquifer is thick, nitrate-rich groundwater may flow below the wetland treatment area, limiting N removal potential (Bohlke and Denver, 1995; Gold et al., 2001). Alternatively, groundwater may pass through reducing sediments at depth where nitrate removal by denitrification may occur before discharging into streams (Bohlke and Denver, 1995). Even adjacent watersheds with similar groundwater nitrate levels can display significant differences in groundwater flow patterns due to variation in local aquifer characteristics (Bohlke and Denver, 1995).

Depressional wetlands are common throughout the upper and middle portions of the Delmarva Peninsula (Clearwater et al., 2000; Fenstermacher et al., 2014) in counties dominated by agricultural land use. The complexity of N fate and transport complicates

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evaluating the effects of depressional wetlands on downstream water quality (Denver et al., 2014). In flat landscapes, groundwater flow paths do not always follow topographic gradients; seasonal reversals in the direction of groundwater flow can cause shallow groundwater to move away from the wetland to the agricultural upland (Denver et al., 2014) (Fig. 2.3). Due to the multidimensionality of groundwater flow and variability in reducing conditions, limited geochemical and hydrologic measurements along a presumed hydrologic transect are often insufficient for determining the potential for nitrate interception and removal in wetlands (Denver et al., 2014).
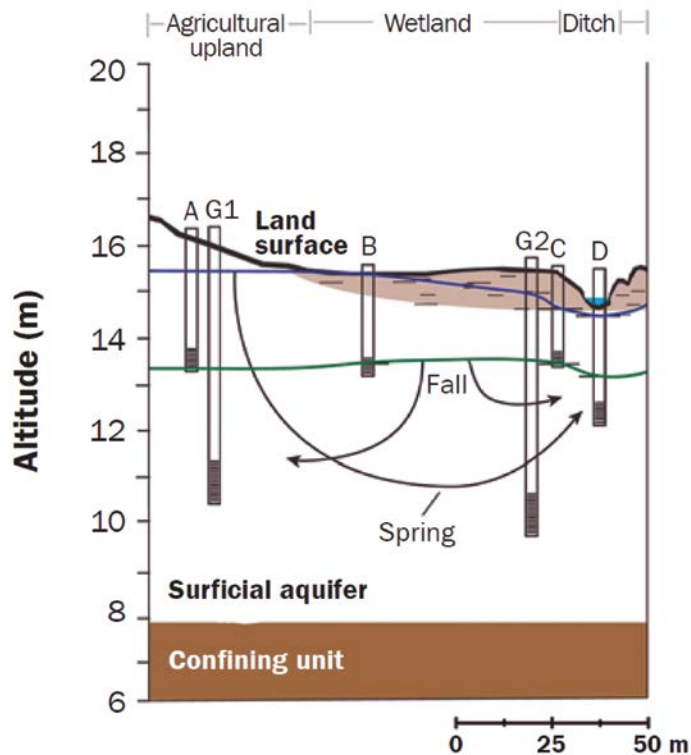
Figure 2.3 Cross section of a prior-converted cropland site illustrating seasonal reversal in hydrologic gradient. *Reprinted, Denver et al. (2014).*

Soil characteristics and geomorphology can provide insight into how aquifer attributes affect groundwater flow and nitrate flux (Gold et al., 2001). For example, research on riparian zones has demonstrated that organic/alluvial deposits show a greater capacity for groundwater nitrate removal than till deposits (Gold et al., 2001; Rosenblatt et al., 2001). In a study of riparian zones in different hydrogeologic settings, Vidon and Hill (2004) demonstrated how landscape characteristics, including upland aquifer depth, slope, and riparian soil texture, can affect the magnitude and duration of nitrate inputs and the potential for nitrate removal in riparian zones. This study highlighted the importance of hydrologic connectivity between upland and riparian areas for nitrate removal; riparian sites with gentle topography, confining layers, and potentially high nitrate removal rates were not important nitrate sinks because of limited water and nitrate inputs from uplands. Method of restoration can affect soil characteristics and the potential for nitrate removal in wetlands as well. For example, confining layers created by the addition of clay or compaction of soils during restoration may limit interaction between anoxic wetland sediments and nitrate in groundwater (Denver et al., 2014).

There is great interest in using remote sensing and geospatial technology to target and monitor wetland restorations using information on topography, hydrology, land cover/use, and soil and aquifer properties. These technologies have successfully been used to predict surface hydrologic processes (Lang et al., 2013, 2012), but developing predictions of groundwater connectivity based on landscape and soil characteristics is more challenging. High resolution Light Detection and Ranging (LiDAR) data allow us to identify terrain attributes with high vertical (15 - 100 cm) and horizontal accuracy (50 - 200 cm), and can significantly improve detection of surface hydrologic connections

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(Lang et al., 2012). Soil data from the Soil Survey Geographic Database (SSURGO) contain information on soil hydrologic properties to a depth of approximately 2 m including hydric rating, soil texture, hydraulic conductivity, available water capacity, hydrologic group, drainage class, organic matter, and bulk density. SSURGO data, however, are considerably coarser (1:12,000 to 1:65,360) than LiDAR data, and their applications in land management planning are limited by the spatial aggregation of soil components. Differences in resolution can lead to problems when overlaying GIS data for mapping and spatial analysis. Spatial aggregation of SSURGO components also creates problems when mapping soil properties for use in landscape analysis. For example, when hydric soil rating is overlain on top of LiDAR data, the coarse resolution of the soil data can conceal the subtle variations in topographic indices of wetness depicted by the LiDAR data. Furthermore, map units often include major and minor components with both hydric and nonhydric soils. A common summarization technique is to assign hydric rating categories based on the cumulative percent composition of all components of a map unit rated as hydric (Fig. 2.4). However, such summarization does not address issues of scale. Due to spatial heterogeneity in hydrologic flow paths and geochemical conditions, finer scale soil property maps would help natural resource managers characterize near-surface hydrologic connectivity between agricultural uplands and wetlands and predict where geochemical conditions may be optimal for restoring wetlands to capture and remove nitrate. The challenge on the Mid-Atlantic Coastal Plain, however, remains that groundwater carrying abundant nitrate is often considerably deeper than 2 m, and aquifer characteristics have not been mapped to sufficient resolution or consistency to predict flow patterns (Ator et al., 2013). Using information compiled from

geophysical and lithologic logs taken across the Delmarva, geologists have mapped the

base of the surficial aquifer at a resolution of 762 m^2, which is too coarse for use at local

scales (Andreason and Staley, 2013).
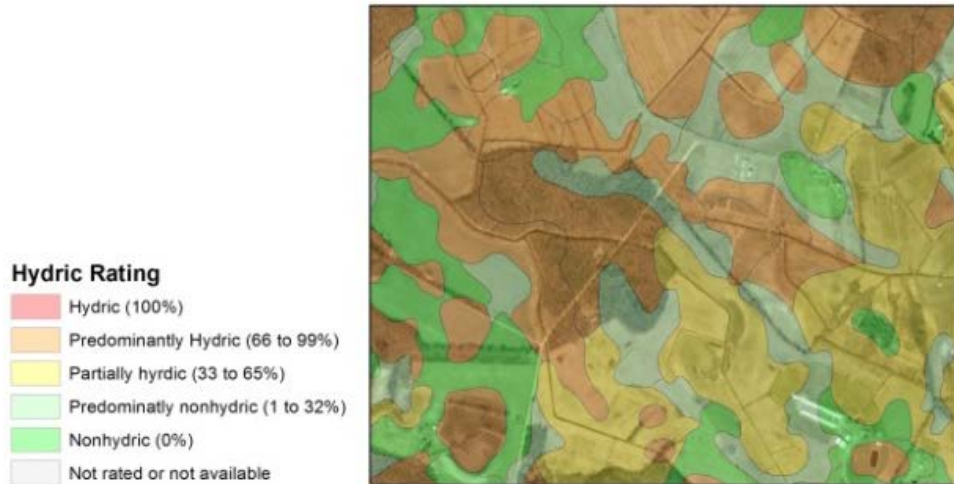
Figure 2.4 NRCS Web Soil Survey hydric soil rating (Soil Survey Staff, 2014a).

2.2.1.1 Proposed Approach

Although we do not currently have the tools to accurately predict ground- water

connectivity between N sources and wetlands at a watershed-scale, there are several

actions we can take to better account for subsurface N transport when siting and

designing BMPs. The following research is recommended in Mid-Atlantic Coastal Plain

watersheds to enhance the implementation of appropriate N management strategies

(detailed below):

1. Assessing hydrologic connectivity in areas with artificial drainage

2. Catchment-scale studies of hydrogeomorphic predictions of hydrologic connectivity

3. Improved use of geospatial data for predicting subsurface connectivity between N sources and wetlands

2.2.1.1.1 Assessing Hydrologic Connectivity in Areas with Artificial Drainage

Hydrologic connectivity in the Mid-Atlantic Coastal Plain is highly influenced by artificial drainage, but there have been a limited number of studies examining nitrate delivery to and from artificial drainage ditches (Schmidt et al., 2007; Vadas et al., 2007). Schmidt et al. (2007) found that shallow ditches on a research farm in southern Delmarva received negligible amounts of subsurface flow inputs; therefore management practices designed to impact groundwater flow would be ineffective in these locations. By contrast, wetlands, riparian buffers, denitrification walls, and controlled drainage structures would likely be effective at mitigating groundwater nitrate moving into deep ditches (Schmidt et al., 2007). Further research examining factors affecting hydrologic transport of N to ditches, including the relative importance of lateral matrix flow and preferential flow in different hydrogeologic settings, would help us identify opportunities to capture and treat nitrate before it reaches the ditch. In cases where ditches intercept groundwater nitrate, wetland restoration adjacent to ditches may help maintain anoxic conditions beneath ditches (Denver et al., 2014), thereby encouraging denitrification in ditch soils and sediments. Controlled drainage structures installed in ditches manage drainage outflow and may enhance denitrification. We recommend testing different designs in order to maximize the effectiveness of these BMPs.

2.2.1.1.2 Catchment-Scale Studies of Hydrogeomorphic Predictions of Hydrologic Connectivity

Different hydrogeomorphic regions on the Mid-Atlantic Coastal Plain display unique groundwater flow and water quality patterns (Hamilton et al., 1993). The highest nitrate concentrations are found in groundwater beneath agricultural areas where the soils and surficial aquifer are composed of sandy, permeable sediments with little clay. Groundwater nitrate is particularly high in the "well-drained uplands," a hydrogeomorphic region characterized by narrow incised streams, deep water tables (>3 m below land surface), and oxic groundwaters. In the "poorly drained uplands" where stream incision is minimal and the water table is within 3 m of land surface, mixing of aerobic and anaerobic groundwater results in lower nitrate concentrations. The lowest groundwater nitrate concentrations are found in regions where organic matter is abundant and clay and silt deposits inhibit downward flow, including the "fine-grained lowlands" and parts of the "surficial confined" region (Hamilton et al., 1993). Different N management strategies may be targeted in different hydrogeomorphic regions. Opportunities for wetland restoration BMPs will likely be greatest in the "poorly drained uplands" and "surficial confined" regions, where the water table is close to the surface and much of the land is in agriculture. This includes much of the central peninsula (Fig. 2.5).

Where sediments are highly permeable and nitrate contamination in deeper groundwater is high, identification of groundwater discharge sites may be important for capturing nitrate. Where clay and silt deposits inhibit downward flow, identification of preferential flow paths in the shallow sub- surface may be more important for intercepting nitrate, and

it may be more feasible to predict subsurface connectivity based on local variability in soil and landscape attributes. Soil moisture predictions are significantly improved when both soil morphological properties and terrain attributes are considered (Takagi and Lin, 2012). The relative importance of soil and terrain parameters in controlling soil moisture varies seasonally and with depth (Takagi and Lin, 2012). Therefore, catchment-scale studies of nitrate transport in different landscape settings are needed to improve our understanding of how topography and soil characteristics affect seasonality of hydrologic connections and the direction and depth of subsurface flow paths.
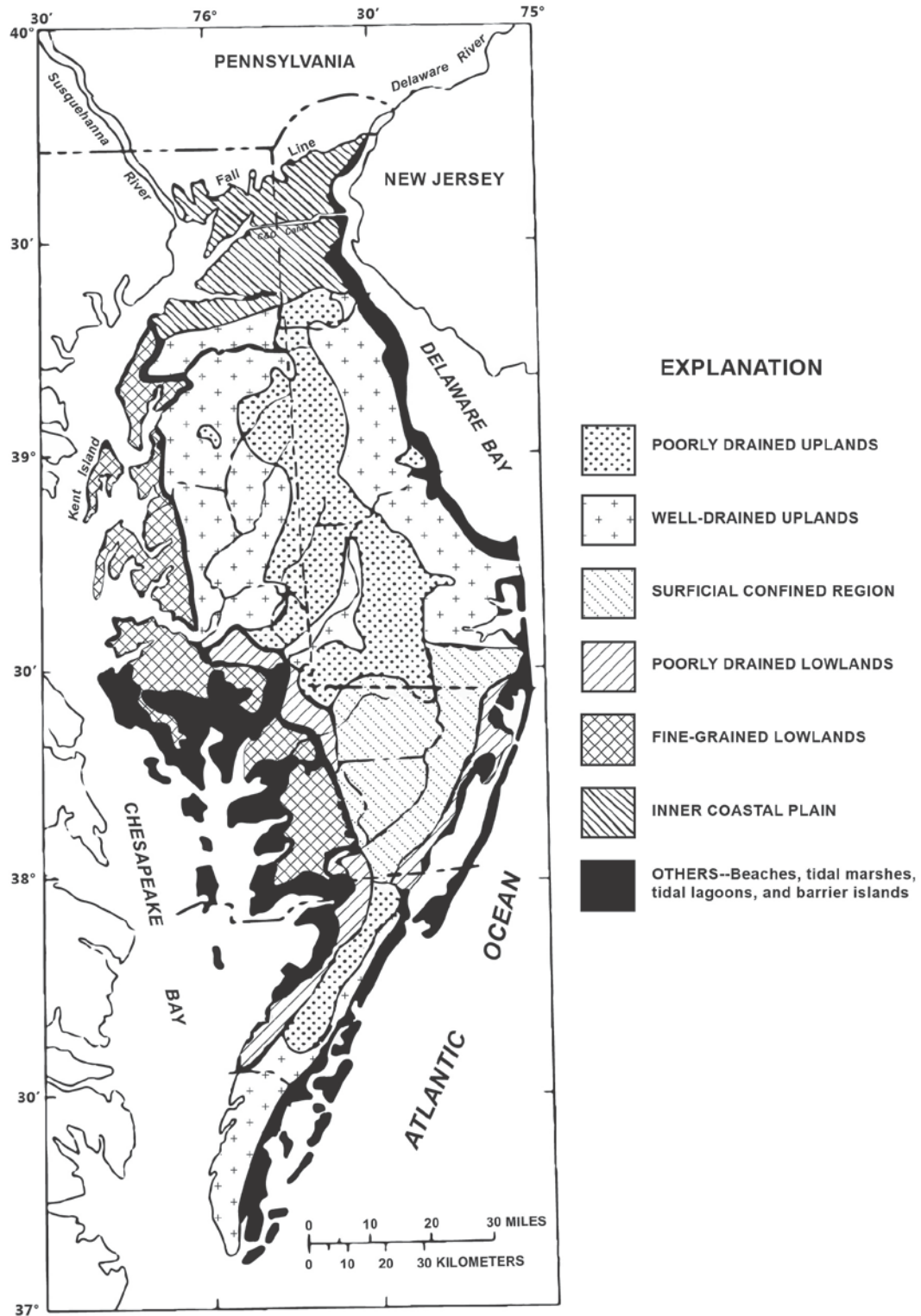
Figure 2.5 Hydrogeomorphic regions in the surficial aquifer in the Delmarva Peninsula. *Image produced by the US Geological Survey, modified from Hamilton et al. (1993).*

Assumptions of lateral subsurface flow need to be reexamined and better accounting of

vertical flow processes and mixing of deeper "old" and shallower "new" groundwater is

needed to improve our understanding of subsurface nitrate loss to surface waters. Trends

in water chemistry can reveal patterns in nitrate fate and transport. McCarty et al. (2014)

found that the relationship between nitrate-N concentration and metolachor metabolite, a

stable, water-soluble herbicide degradation product, could be used to distinguish between

dilution and denitrification effects on nitrate concentrations in surface waters of the

Choptank River watershed. These patterns can help us identify watersheds where

denitrification may be enhanced by restoring wetlands (McCarty et al., 2014).

In addition to nitrate removal, wetlands may improve water quality in local streams

through mixing and dilution (Denver et al., 2014). Forested wetlands upgradient from

agriculture can be a source of low nitrate water to downstream waters, diluting nitrate

concentrations and improving regional water quality (Denver et al., 2014). Thus,

identifying opportunities to dilute groundwater nitrate by restoring hydrology to ditched

forested wetlands will likely be an important component of a watershed approach to

wetland restoration.

2.2.1.1.3 Improved Use of Geospatial Data for Predicting Subsurface Connectivity
between N Sources and Wetlands

The success of a watershed approach to wetland restoration and creation will depend

greatly on the effective use of geospatial data. Recent advances in geospatial technology

and greater access to high resolution data allow for better mapping of landscape factors

influencing the fate and transport of nitrate. New GIS-based targeting tools are continually being developed to identify priority areas for wetland restoration (Hunter et al., 2012; Tomer et al., 2013; White and Fennessy, 2005). There are several ways to improve current use of geospatial data to better identify areas where the hydrology may favor N removal by restored/created wetlands. These are explained in the following sections.

2.2.1.1.3.1 Expanded Use of LiDAR Data and Topographic Indices Derived from LiDAR

High-resolution LiDAR data are available for much of the Mid-Atlantic Coastal Plain and can improve detection of saturated areas in the landscape and hydrologic connections between wetlands and surface waters (Lang et al., 2012). Tomer et al. (2013) used LiDAR topographic data in combination with output from water quality models to identify feasible locations for wetlands in an Illinois watershed and esti- mate watershed nitrate loads if they are constructed. Topographic metrics derived from LiDAR can be used to predict spatial patterns in soil saturation and map wetlands (Lang et al., 2013). The topographic wetness index, which is based on upslope contributing area and slope, can be generated using a number of different flow routing algorithms. In a raster layer, there are eight directions in which water can flow. GIS programs often use the D8 algorithm, which directs water to the steepest downslope neighboring cell. Other algorithms use more complex decision rules to direct flow to neighboring cells. Distributed flow patterns may better predict flow in relatively flat landscapes (Lang et al.,

2013). The topographic wetness index will be most useful in areas with a confining layer, where lateral flows dominate vertical flows (Lang et al., 2013). Other topographic metrics such as relief and curvature may also help predict extent and frequency of inundation. Further testing of these metrics in different landscapes is needed to deter- mine how they can best be incorporated into wetland planning (Lang et al., 2013).

2.2.1.1.3.2 Better Use of Soil Data

The SSURGO database provides information on a range of soil hydrologic properties to a depth of approximately 2 m. Wetland restoration planners often rely on hydric soils maps, but data on soil texture, hydraulic conductivity, available water capacity, hydrologic group, drainage class, bulk density, and organic matter are also available through SSURGO. These attributes may account for spatial and temporal variability in soil moisture that is not captured by topographic indices, and help planners predict hydrologic connectivity across the land- scape. For example, drainage class can indicate the duration and seasonality of saturation in potential wetland sites. Textural differences in soil layers may indicate preferential flow mechanisms that have important implications for solute transport (Steenhuis et al., 1998).

Although SSURGO currently provides the most detailed soil geographic data in the US, its applications in land management planning are limited by its coarse scale and the spatial aggregation of soil components. SSURGO data consists of polygons representing map units and tabular soil property data associated with distinct components within each

map unit. A single SSURGO map unit may contain several major and minor components, each associated with different soils with contrasting properties.

The recent development of gSSURGO, a raster soil dataset prepared by merging vector-based SSURGO data and tabular data, will make it easier for conservation planners to map these attributes and combine soil information with other datasets. The potential wetland soil landscapes (PWSL) raster layer is an excellent example of the utility of this new dataset (Fig. 2.6). The PWSL expands on hydric soil rankings by identifying soils that were historically hydric based on additional soil attributes. For example, if a pixel falls within a map unit in which the dominant component is not identified as being hydric, the pixel is classified as PWSL if the drainage class is "poorly drained" or "very poorly drained" or the map unit name contains the phrase "ditched" or "drained" (Soil Survey Staff, 2014a). This dataset could provide a basis for identifying sites where wetland hydrology can most readily be restored. PWSL data could be combined with topographic, stream, and land use data to further improve characterization of hydrology and factors contributing to nitrate loss.
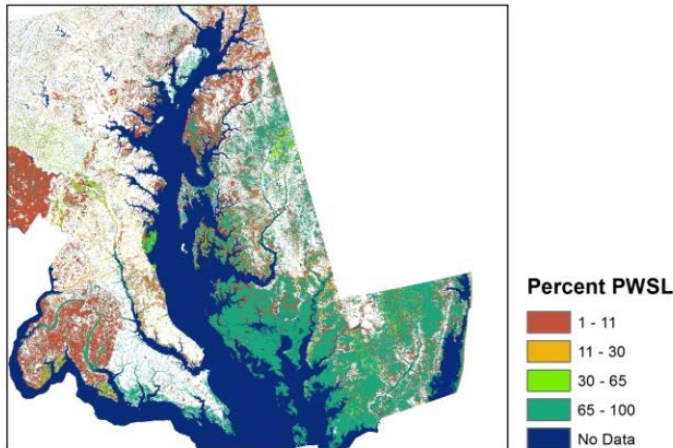
Figure 2.6 gSSURGO potential wetland soil landscapes (PWSL) (Soil Survey Staff, 2014b).

Another promising development in soil mapping is the disaggregation of soil map units into probabilistic raster maps of individual components. The distribution of components can be estimated based on correlations with environmental variables such as terrain position, parent materials, topography, and other landscape factors (Nauman and Thompson, 2014; Subburayalu et al., 2014). For example, Nauman and Thompson (2014) queried geomorphic and hillslope profile descriptors in the SSURGO database and developed rules based on environmental raster values for the component landform descriptions for a 3877 km^2 study area in the Appalachian Mountains of West Virginia. These relationships were then used to build a set of training areas for all components, which were used in classification trees with additional environmental rasters to transform the original SSURGO soil map into a gridded soil component map (Fig. 2.7). Disaggregation has the potential to provide land use planners with more detailed soil maps that better represent spatial variation in soil attributes while reducing the amount of work required to use soil survey data in conservation planning. A similar approach could

be developed using environmental rasters such as LiDAR-derived topographic metrics to identify historic wetlands where the hydrology can most readily be restored.
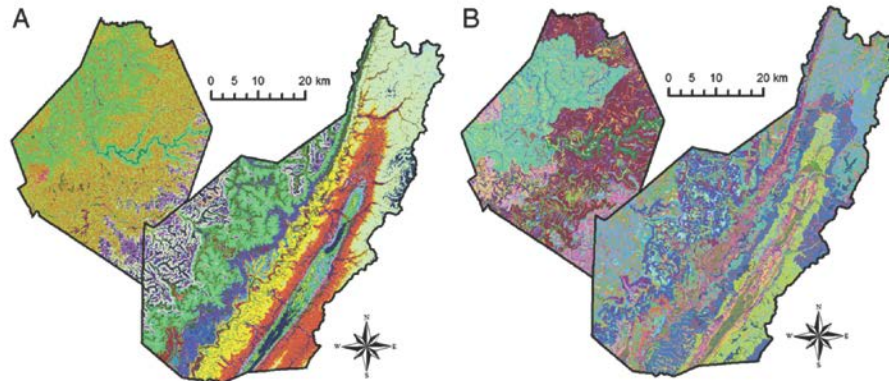
Figure 2.7 Maps comparing disaggregated SSURGO product (A) with original soil survey map units (B). *Reprinted with permission, Nauman and Thompson (2014).*

2.2.1.1.3.3 Incorporation of Ditch Network Data

Ditch network data can help identify areas promoting rapid transport of nitrate to streams by ditches. The Eastern Shore Regional GIS Cooperative has digitized tax ditches maintained by public drainage associations in select watersheds, and the data are available for free download (Eastern Shore Regional GIS Cooperative, 2004). As demonstrated by Schmidt et al. (2007), these deeper ditches receive continuous subsurface inputs from upland agricultural fields and can be important conduits for the accelerated delivery of nitrate to surface waters. Field ditches have also been digitized in several watersheds as part of Chesapeake Conservancy's effort to advance the use of

geospatial technologies in conservation planning across the Chesapeake Bay watershed
(Chesapeake Conservancy, 2014).

2.2.1.1.3.4 Incorporation of Remote- and Ground-Based Sensor Techniques for Measuring Variability in Soil and Vegetation Characteristics

Remote sensing offers a rapid, cost-effective way to incorporate spatial and temporal information on landscape attributes into wetland restoration planning. Advances in technology and new interpretation techniques have led to improvements in wetland mapping and detection of changes in hydrology, vegetation, and other surface characteristics (Klemas, 2013, 2011; Lang et al., 2008). Although limited primarily to studying changes in surface characteristics, remote sensing has great potential to assist conservation planners in restoration targeting. Airborne and high-resolution satellite imagers may be useful in siting and monitoring small wetlands. Satellite sensors such as IKONOS and QuickBird can provide resolutions of 0.5 - 1 m in panchromatic bands and 2 - 4 m in multispectral bands in the visible and near-infrared regions of the electromagnetic spectrum (Klemas, 2011). Color infrared aerial photography and multispectral and hyperspectral imagery may be useful in studying vegetation characteristics that can be related back to wetland function (Klemas, 2013; Tuxen et al., 2008). Indices such as the normalized difference vegetation index, which uses the red and near-infrared bands to detect the spectral characteristics of green plants, can be used to map spatial patterns in crop biomass (Hively et al., 2009). Patterns in crop biomass during dry and wet years may be good indicators of the hydrology of historic wetlands.

Multitemporal synthetic aperture radar (SAR) is particularly promising for wetland studies. SAR microwave energy is sensitive to variations in soil moisture and can pass through vegetation with little attenuation (Klemas, 2013). Lang et al. (2008) demonstrated how multitemporal C-band SAR can be used to detect seasonal changes in hydrologic characteristics of forested wetlands. SAR data are potentially useful for monitoring temporal fluctuations in soil moisture and wetland inundation on prior converted cropland (former wetlands drained for agricultural production). These data could also help us understand the role of forested wetlands upgradient of cropland in diluting nitrate concentrations in local streams.

At field scales, geophysical tools such as ground penetrating radar (GPR) and electromagnetic induction (EMI) can be used to map soil physical properties. Gish et al. (2002) used GPR-derived subsurface digital elevation models (DEMs) to identify preferential flow pathways based on depth to a subsurface clay layer. Subsurface restricting layers within 2 m of the surface benefited corn grain yields during a drought year. Yields decreased with increasing horizontal distance from the GPR-identified flow pathways.

GPR is often used in combination with EMI, which measures soil electrical conductivity (ECa). ECa is affected by factors such as soil moisture, clay content, and mineralogy, which can be used to differentiate soil components (Zhu et al., 2013). Recent studies have explored the application of these technologies in combination with in-field measurements to evaluate the effects of agricultural practices on soil properties (Jonard et al., 2013) and advance site-specific management for precision agriculture (Zhu et al., 2013). Using similar methods, geophysical tools could be used to evaluate potential restoration sites on

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prior-converted cropland. Testing of these technologies in different landscape settings is needed to better understand how to use these tools.

Continued advances in geospatial technology and remote- and ground- based sensing will likely improve our ability to predict where in the landscape restoring the hydrology of historic wetlands will promote denitrification or nitrate dilution. Integration of local knowledge with geospatial tools may provide for the most robust analysis of landscapes.

2.2.2 Estimating Wetland Efficiencies

Wetland efficiencies use simple relationships to predict N removal rates. N removal efficiencies allow conservation planners to make estimates of N attenuation at the watershed scale based on a few selected parameters that are readily available. Efficiencies also allow for directly comparing different N management options to select the most cost-effective choice in terms of dollars per kilogram of nitrogen removed, facilitating policy making and documentation of progress toward achieving TMDLs.

Wetland efficiencies for N are difficult to obtain for a number of reasons. First, nitrate removal efficiencies reported in the literature are highly variable, ranging from negative efficiencies (export of nitrate from the wetland) to greater than 90% nitrate removal (O'Geen et al., 2010). Efficiencies vary with wetland characteristics, climate, landscape position, N loading rates, objectives of restoration, and other factors (O'Geen et al., 2010). Despite the vast number of studies done on the use of wetlands for nutrient treatment, little research has been done on wetlands treating agricultural nonpoint source pollution, and only a handful of studies have been done in the Chesapeake Bay

watershed. Efficiency estimates are often based on individual wetlands under highly

managed conditions. Whether significant N removal can be achieved at the watershed

scale has not yet been tested in the Chesapeake. For modeling purposes, the ratio of

wetland to watershed area is commonly used as a surrogate for hydrologic retention time

in estimating efficiencies due to the correlation between these variables, but this approach

ignores site-specific conditions that can affect N removal, such as the amount of carbon

available for denitrification, the permeability of upland and wetland sediments, and local

subsurface connectivity.

The challenge of estimating efficiencies at the watershed scale is exemplified by the

Chesapeake Bay Watershed Model. Wetland BMPs are assigned efficiencies based on a

relationship between percent N removal and wetland area as a percentage of the

contributing watershed. Efficiencies are based on geomorphic province, with the

assumption that the wetland to watershed area ratio increases moving from upland to

low- land regions (Simpson and Weammert, 2009). Wetland BMPs in the Coastal Plain

are assigned an efficiency rating of 25%, based on a 4% wetland to watershed area ratio;

in the Piedmont Plateau a rating of 14% based on a 2% ratio; and in the Appalachian

Plateaus a rating of 7% based on a 1% ratio. These efficiencies were derived through

regression analysis of data from 16 studies, only one of which was conducted in the

Chesapeake Bay watershed. The model, based on first-order kinetics, fits the data only

weakly (Figure 2.8) and does not capture other factors affecting efficiencies such as

wetland age, seasonal variation, flow variability, landscape position, land use conversion,

and sediment accumulation (Simpson and Weammert, 2009). When developed, it was

expected that these efficiencies would continue to be refined, but without monitoring

programs in place to assess wetland performance under different conditions, we have few

regional or local data for developing and validating efficiency models.
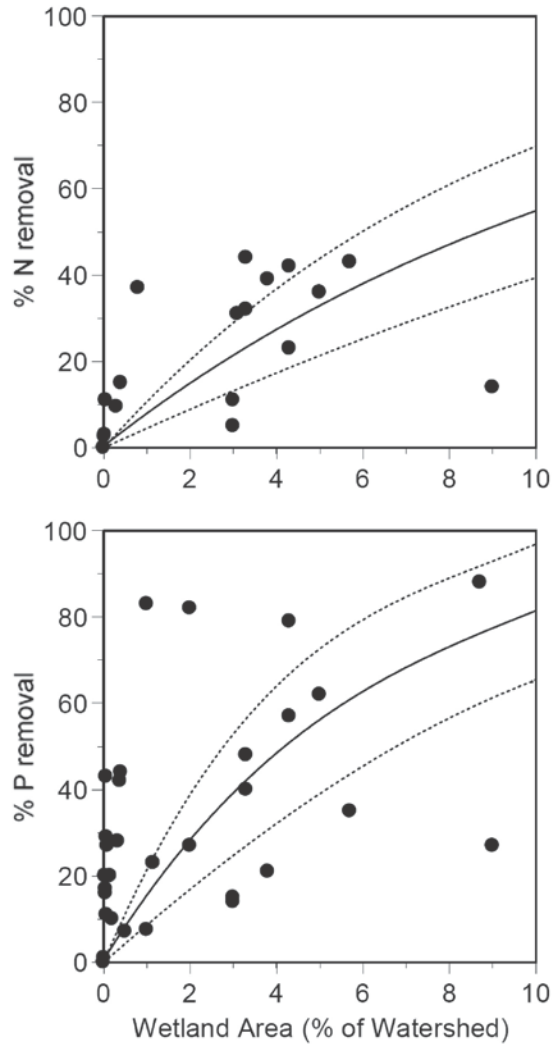
Figure 2.8 Percentage of nutrients removed annually versus wetland/watershed ratio.
Reprinted with permission, Simpson and Weammert (2009).

A second challenge to estimating wetland N removal efficiency is accounting for

seasonality of nutrient discharges. Depending on climate and geomorphic setting, the

volume and timing of runoff will vary throughout the year. N loss may be event-driven

(Kovacic et al., 2000) or it may be attributed to baseflow (Ator and Denver, 2012), warranting different wetland designs and efficiencies. For example, in constructed wetlands receiving tile drainage on the Embarras River in Illinois, the greatest tile discharges and nutrient fluxes occur during pulse flows in the spring and winter seasons (Kovacic et al., 2000). By contrast, in depressional wetlands in the Choptank watershed in Maryland, N fluxes depend on the depth and gradient of the water table, which vary seasonally and are controlled by a complex set of geologic, geochemical, and hydrologic conditions (Denver et al., 2014). In general, N loading in wetlands is likely to be lowest in the summer when crop uptake and microbial activity are greatest. In depressional wetlands on the Mid-Atlantic Coastal Plain, N removal efficiencies will be the greatest when the groundwater flows consistently from the agricultural upland to the wetland and passes through reducing soils within the wetland. With a better understanding of seasonal variability in nutrient fluxes in wetlands in different settings, a seasonal correction factor may help improve efficiency estimates (Simpson and Weammert, 2009).

Finally, diverse wetland types and approaches to restoration will lead to variability in N removal efficiencies. On the Mid-Atlantic Coastal Plain, denitrification potential varies with wetland hydrogeomorphic type (riverine, depressional, flat) (Jordan et al., 2007). Method of restoration/creation may impact how quickly water quality functions are achieved. For example, ditch plugging causes little disturbance to the soil, but may divert nitrate-rich groundwater to a new groundwater flow path (T. Jordan, 2013, pers. comm.). Scraping, by contrast, removes organic-rich surface horizons, exposing subsurface horizons. After scraping, some of the topsoil is often replaced, or imported materials such

as sand, straw, or compost are added. Restoration methods will likely affect the amount of carbon available for denitrification and the degree of surface-groundwater interactions.

2.2.2.1 Proposed Approach

Nitrogen removal is most affected by hydraulic loading rate, residence time, nitrate concentration, nitrate loading rate (Crumpton et al., 2006), and carbon availability. A better understanding of how these factors and wetland design affect wetland performance in different hydrogeomorphic settings would help us to develop improved N removal efficiency estimates. As discussed previously, accounting for subsurface flows to, within, and from wetlands is a challenge on the Mid-Atlantic Coastal Plain. We recommend that developing reliable estimates of hydraulic and nitrate loading rates be a priority moving forward. Selective monitoring of wetlands representing a range of environmental conditions would provide documentation of nitrate reduction and data to calibrate models of N removal in wetlands. This is similar to the approach being taken in Iowa to advance watershed-based wetland restoration and construction for water quality improvement in the Mississippi River Basin (Crumpton et al., 2006) (see following section).

2.3 Political, Social, and Economic Challenges

In addition to biological and physical challenges, there are a number of political, social, and economic challenges to using wetlands to improve water quality in agricultural watersheds. These include (1) limited information on current wetland practices, (2)

broad/unclear objectives of wetland BMPs, and (3) factors limiting landowner willingness to adopt wetland BMPs. Within these challenges, there are questions such as

- How well do existing institutions support wetland targeting for N attenuation?
- How can we ensure that wetlands are maintained so that they continue to provide the expected benefits?
- How do wetlands fit within the broader response strategy for reducing nutrient loads in the Chesapeake Bay watershed?

2.3.1 Limited Information on Current Wetland Practices

Wetland practices are supported largely by USDA Farm Bill programs that provide technical and/or financial support to landowners. These voluntary cost-share programs include the Conservation Reserve Program (CRP) and Conservation Reserve Enhancement Program (CREP), the Environmental Quality Incentives Program (EQIP), the Wetland Reserve Program (WRP), and the Wildlife Habitat Incentives Program (WHIP) (Table 2.1) with the majority of wetland restorations implemented under CRP/CREP and WRP (De Steven and Lowrance, 2011). Wetland projects are also supported by regional and state programs such as the Chesapeake and Atlantic Coastal Bays Trust Fund, Chesapeake Bay Trust, and the National Fish and Wildlife Foundation's Chesapeake Bay Stewardship Fund.

In 2003, the USDA initiated the Conservation Effects Assessment Project (CEAP) to quantify the benefits of conservation practices implemented under the Farm Bill. CEAP includes a wetland component aimed at assessing the effectiveness of wetland practices

in providing ecosystem services through several regional and watershed-scale studies (Brinson and Eckles, 2011). The CEAP Wetlands Mid-Atlantic study has been underway since 2008 with data collection ongoing on restored and natural wetlands and prior converted cropland in Delaware, Virginia, and Maryland. CEAP's effort has been limited in the Piedmont and North Atlantic Coastal Plain by a lack of information on how conservation practices are implemented in the field (De Steven and Lowrance, 2011). Farm Bill conservation programs do not require monitoring of conservation benefits, and since projects are carried out on private land and farmer privacy is protected under Section 1619 of the Food Security Act, opportunities for research have been limited prior to CEAP. Detailed spatial data on wetland practices would allow us to more fully quantify the effects of wetlands on water quality at watershed scales (Gleason et al., 2011), but this information is not publicly available for most programs (WRP easements are the exception). Information on Farm Bill expenditures on these practices, beyond overall program expenditures, is not reported either (USDA Natural Resources Conservation Service, 2013). Expenditures on wetland practices could help us evaluate the cost-effectiveness of these BMPs at county, state, and regional scales.

Table 2.1 Farm Bill conservation programs.

Program	Incentive type	Contract period (yr)
Conservation Reserve Program (CRP)	Annual rents plus cost share	10-15
Conservation Reserve Enhancement Program (CREP)	Annual rents plus cost share, easements	10-15
Wetland Reserve Program (WRP)	Cost share or one-time easement plus cost share	10 yr contract; 30 yr/permanent easement
Environmental Quality Incentives Program (EQIP)	Cost share	1-10
Wildlife Habitat Incentives Program (WHIP)	Cost share	1-10 and 15+

2.3.1.1 Proposed Approach

We recommend that monitoring plans be built into conservation programs. Following the recommendations of CEAP, monitoring programs should (1) specifically evaluate response to treatment (i.e., nitrate reduction through wetland treatment), (2) monitor conservation practices as intensively as water quality (i.e., through documentation of wetland restoration methods and maintenance), and (3) invest in long term monitoring and technical expertise (Osmond et al., 2012). A coordinated monitoring program could be conducted on a representative subset of wetlands, across a range of geomorphic and climatic settings. Measurements of inflow and outflow rates, nitrate concentrations, and temperature could be collected regularly throughout the year to account for seasonal variability in nitrate removal. With time, these measurements could be used to calibrate models of wetland performance in different landscapes. The monitoring program employed by Iowa CREP (see Box 2.1) may serve as a role model for the Chesapeake

Bay watershed. Alternatively, a program could be established whereby landowners monitor wetlands themselves, with appropriate technical oversight by the Natural Resources Conservation Service (NRCS) or partner organizations to ensure data quality. To our knowledge, this has not been tested, but it is possible that landowners would be willing to have wetlands on their property monitored so that they could document reductions for their nutrient management plans.

Box 2.1 Iowa conservation reserve enhancement program

The Iowa Conservation Reserve Enhancement Program (CREP) is an excellent example of how water quality monitoring can be built into a wetland conservation program. These CREP wetlands are strategically located and designed to remove nitrate from tile-drained cropland (Iowa Department of Agriculture and Land Stewardship, 2013). Representative wetlands are monitored each year to document nitrate reduction (Crumpton et al., 2006). Wetlands selected for monitoring range from 0.5% to 2% wetland/watershed ratio and 10 to 30 mgl^{-1} average input nitrate concentrations (Crumpton et al., 2006). Weekly grab samples are taken from each wetland, and automated samplers and flow meters are installed at inflows and outflows at a subset of wetlands. In addition, water levels are monitored continuously at outflow structures and water temper- ature is continuously recorded. In support of the CREP monitoring program, mass balance analysis and modeling are used to estimate variability in performance of CREP wetlands based on temperature and precipitation patterns (Crumpton et al., 2006). These CREP wetlands reportedly remove 40% to 90% of nitrate inputs (Iowa Department of Agriculture and Land Stewardship, 2012).

In addition to a coordinated monitoring program, we propose that standards for recordkeeping be established to compare siting and design methods. At a minimum, pre-restoration conditions (soils, hydrology, vegetation), methods of restoring hydrology, degree of earth-moving, addition of imported materials, and actual costs should be recorded in order to better evaluate practices and make future recommendations.

Finally, we suggest that program expenditures be reported along with enrollment by acreage and count. Expenditure data would help us assess how programs are allocating their funds, and compare how much funding is available for wetland restoration/creation with how much is spent. Expenditure data would also allow for better accounting of the cost of wetland practices and help planners determine which programs are most cost-effective with regard to implementing wetland BMPs for water quality improvement.

2.3.2 Broad/Unclear Objectives of Wetland BMPs

A number of wetland practices are available through WRP, CRP, EQIP, and WHIP, four of which are considered water quality BMPs: wetland construction, wetland restoration, wetland creation, and wetland enhancement (Table 2.2). The emphasis of these practices has traditionally been on provision of waterfowl and wildlife habitat, with little attention given to water quality in siting and design (Crumpton et al., 2006; De Steven and Gramling, 2012). Wetland construction (656), the only Farm Bill wetland practice whose explicit purpose is to reduce agricultural runoff, is not yet an approved practice in any of the Bay states, although the Maryland NRCS is currently considering adding it to the list of approved CREP practices (S. Strano, 2012, pers. comm.).

Table 2.2 Wetland conservation practice standards.

NRCS Cons. Practice Standard	Purpose
Constructed Wetland (656)	To reduce pollution potential of runoff and wastewater from agricultural lands to water resources
Wetland Restoration (657)	To restore wetland function, value, habitat, diversity, and capacity to a close approximation of the pre-disturbance conditions by restoring: conditions conducive to hydric soil maintenance, wetland hydrology, native hydrophytic vegetation, original fish and wildlife habitats
Wetland Creation (658)	To establish wetland hydrology, vegetation, and wildlife habitat functions on soils capable of supporting those functions
Wetland Enhancement (659)	To increase capacity of specific wetland functions by enhancing hydric soil functions, hydrology, vegetation, enhancing plant and animal habitats

The degree to which water quality is addressed in restoration depends on the program and on the priorities of local and state governments. CREP program guidelines limit enrollment to eligible cropland containing prior-converted and farmed wetlands, while the WRP allows eligibility of hydrologically degraded wetlands on rangeland and forest production lands as well. In Maryland, WRP projects often consist of plugging ditches on forested land that does not receive agricultural N. These restorations remove little, if any, N from upland areas, although they may help improve regional water quality through dilution with low-nitrate water (Denver et al., 2014).

Priorities of local conservancies and wildlife organizations also direct wetland restoration objectives. For example, Ducks Unlimited has frequently partnered with the US Fish and Wildlife Service and local agencies to restore wetlands, with the objective of creating waterfowl habitat (Ducks Unlimited, 2014). The Nature Conservancy (TNC) is actively involved in wetland restorations, working with federal and local agencies and landowners to carry out targeted restoration efforts to improve water quality and wildlife habitat (The

Nature Conservancy, 2014). TNC has developed a LiDAR-based targeting tool to site wetlands where they can intercept nutrient and sediment runoff (The Nature Conservancy, 2013). By working with scientists, conservation, planners, and other stake-holders, these efforts can help direct conservation program resources toward projects that have greater potential to achieve improvements in water quality.

Several of the state WIPs include specific levels of wetland restoration by 2025 to help meet the Chesapeake Bay TMDL, including Maryland (6000 ha), Virginia (7776 ha), Delaware (2317 ha), New York (5581 ha), Pennsylvania (21,908 ha), and West Virginia (164 ha) (D. Hopkins, 2014, pers. comm.). WIPS are developed in consultation with local partners at the county scale (Maryland Department of the Environment, 2012); so planned wetland acreage should represent the combined amounts of individual county wetland goals. It is not clear how WIP planners arrived at these acreage goals and whether all of these projects include water quality as an explicit objective. For example, some WRP projects may be included that are not situated to receive significant agricultural runoff (USDA NRCS, 2012, pers. comm.; MDE, 2012, pers. comm.). Most wetland conservation practices have broad objectives, and water quality improvement is often an assumed benefit of restoring wetland hydrology, rather than an explicit objective. Restoration calls for the "return of a wetland and its functions to a close approximation of its original condition as it existed prior to disturbance" (USDA Natural Resources Conservation Service, 2014). It may be unrealistic to expect though that in working agricultural landscapes, we can recreate historic wetland conditions (Zedler, 2003). Prioritizing nutrient removal may conflict with other wetland functions, such as provision of wildlife habitat (Brinson and Eckles, 2011). For example, wetlands receiving high N

and P inputs can become dominated by monocultures of *Typha* spp. or similarly aggressive plant species (Woo and Zedler, 2002). Thus, establishing objectives and evaluating wetland success will require consideration of the multiple services wetlands provide and balancing the demands of the TMDL with additional local, state, and regional priorities.

2.3.2.1 Proposed Approach

Wetlands provide a number of ecosystem services, including filtering nutrients and sediments, providing wildlife habitat, flood control, and carbon sequestration – all of which are valuable restoration outcomes but may not all be achievable in any given project. The WIPs are intended to document how Bay jurisdictions will achieve nutrient reductions needed to meet the TMDL. We propose, therefore, that wetland restorations credited in WIPs include the explicit objective of improving water quality in project siting and design.

Programs that seek to reduce nonpoint source pollution, such as CREP, may be best suited for implementing these restorations. Alternatively, Bay states could issue a directive establishing that WRP, CRP, and other wetland projects that are credited toward WIP wetland acreage include water quality as an objective. Performance-based evaluation through monitoring of select projects would add value by enabling Bay jurisdictions to document nutrient reductions, develop estimates of efficiency for different geomorphic and hydrologic settings, and strategize placement of wetlands.

2.3.3 Landowner Willingness to Adopt

Farm Bill programs are voluntary, with landowners typically approaching local soil

conservation districts to get support for implementing conservation practices. Some

programs, such as the Virginia CREP, have used a targeting approach to direct outreach

efforts toward landowners with eligible acreage (E. Horsley, 2013, pers. comm.). One of

the greatest challenges moving forward with a watershed approach to wetland restoration

will be the degree to which landowners are willing to adopt these practices. Possible

obstacles to landowner participation need to be explored in order to develop educational

programs on wetlands and water quality and direct outreach efforts toward those people

most likely to adopt practices (David et al., 2013). Although no systematic study of

farmer attitudes toward wetlands has been conducted in the Chesapeake Bay watershed,

reports from other regions as well as research on agricultural BMP adoption provide

insight into farmers' perceived costs of wetlands and factors that might impede adoption.

A recent study in Sweden identified "land management in the best possible way" as the

primary motive of farmers considering constructing a wetland on their land (Hansson et

al., 2012). Farmers surveyed in this study viewed food production as the ultimate use of

the land, and thought productive land should be kept in cultivation. Land that is

unproductive or marginally productive could be considered for other income-generating

activities. In the US, high commodity prices incentivize farmers to plant on all arable

land, including land with poor drainage where crop success is highly variable year to

year. Farmers in Kansas reported wetland areas can be harvested three years out of five

with only slightly below average productivity (Gelso et al., 2008). In the Mid-Atlantic

Coastal Plain, in a dry year the wetter areas – areas where wetlands would be targeted –

are often the farmers' most productive land. The challenge, therefore, is to identify the value farmers place on these areas.

- How does the value vary with frequency and duration of saturation?
- Under what conditions are these lands considered marginal or unproductive?

Producers see themselves as stewards of the land, but economic and other objectives may outweigh stewardship goals (David et al., 2013). Farmers must consider their decision to adopt a given BMP within the context of their entire farm operation (David et al., 2013). Meeting the needs of landowners may limit options for wetland siting and design. However, in some instances, it may be desirable to take "productive" land out of production to achieve water quality benefits. It may be necessary to expand the concept farmers have of land productivity to include ecosystem services other than food production, as recommended by Hansson et al. (2012).

Several other deterrents to wetland restoration can make obtaining landowner cooperation difficult. Gelso et al. (2008) found that a high degree of wetland dispersion on the farm substantially increases the perceived costs associated with wetlands, indicating that farmers are inconvenienced by having to transport equipment around wetland areas. These "inconvenience costs" limit options for siting wetlands at the farm level. For example, the best place to site a wetland to capture nitrate might be in the middle of the field, but the farmer may only be willing to put in a wetland at the edge of the field where it will not be in the way of farm operations.

A related issue is wetland maintenance. The effectiveness of wetlands in improving water quality often depends on the degree to which the wetlands are maintained for this purpose

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(Seitzinger et al., 2006). A long-term view is implicit in a watershed-scale approach, and requires consideration of both the ecological and programmatic lifetimes of conservation practices (Brinson and Eckles, 2011). For wetlands receiving high sediment loads, the ecological lifetime may be particularly short due to loss of surface water storage capacity through sediment infilling (Brinson and Eckles, 2011). A possible solution would be to periodically excavate the wetland, but this may impose additional inconvenience costs on the landowner.

An additional concern shared by many farmers is the possibility of negatively impacting the drainage rights of their neighbors. Maintaining good relations with neighbors can be a priority value among farmers. Uncertainty about the effects of plugging a ditch or otherwise altering drainage on ditch networks may discourage farmers from installing wet- lands. This relates to the larger issue of farmers' understanding of the effects of wetland restoration on hydrology and local and regional water quality.

Farmers may not understand how wetlands contribute to nutrient removal at the farm and watershed scale (David et al., 2013; Hansson et al., 2012). Hansson et al. (2012) reported that interest in wetlands was lower among farmers who knew less about wetland ecosystem services. The traditional focus on the wildlife benefits of wetlands in US conservation programs indicates that farmers may appreciate the wildlife values, and are often persuaded by the hunting opportunities wetlands provide. The water quality benefits are less obvious, particularly since they are so rarely documented. Producers cannot see the loss of nutrients and may feel disconnected from the downstream effects (David et al., 2013). In the Mississippi River Basin, farmers' growing mistrust of policy makers is also a major barrier to collaboration (David et al., 2013). On the other hand, acknowledgment

that a constructed wetland is in fact contributing to nutrient reduction can give farmers a more positive feeling about wetlands, and even a sense of pride and satisfaction (Hansson et al., 2012). This finding provides further justification for the need for a coordinated monitoring program.

2.3.3.1 Proposed Approach

Studies on farmer attitudes in the Chesapeake Bay watershed toward wetlands would help us identify possible barriers to implementing a watershed-scale approach to wetland restoration. Results could be used to target practices that meet the needs of landowners and compare different N management strategies. A monitoring program also has the potential to help us meet this challenge. By directly linking water quality benefits to wetland conservation practices, farmers could document nutrient reductions in their farm operations. Assigning a dollar value to units of nutrients removed through performance-based incentive payments or nutrient trading programs could enhance the perception that wetlands are "productive" and even profitable.

2.4 Conclusions

Due to the large percentage of land in agriculture and the extent of sub- surface drainage, the Mid-Atlantic Coastal Plain is an appealing choice for wetland restoration and creation in the Chesapeake Bay watershed. While the opportunities to restore wetlands in this region are abundant, there are numerous challenges to locating and designing wetlands to

capture nitrate runoff. Due to the heterogeneity of the surficial aquifer, variability in soil hydrologic characteristics, and seasonality of hydrologic connections, accounting for subsurface connectivity between nitrogen sources and wetlands is a challenge. Social, political, and economic constraints further complicate using wetlands to reduce nonpoint source pollution. There are a number of steps we can take to improve the likelihood that wetlands will contribute to water quality goals. Information on subsurface connectivity between nitrogen sources and wetlands is a significant challenge. We believe that this challenge can be addressed through improved assessment of hydrologic connectivity in areas with artificial drainage; conducting catchment-scale studies of hydrogeomorphic predictions of hydrologic connectivity; and improved use of geospatial data for predicting subsurface connectivity between N sources and wetlands including LiDAR, soil survey, ditch network data, and remote- and ground- based sensing techniques. Our poor ability to estimate wetland efficiencies can be addressed by implementing a coordinated monitoring program to assess the success of these projects across environmental conditions and management practices. Such a monitoring program would also provide needed information on the implementation of wetland practices supported through government programs. The use of programmatic information would also be improved with better recordkeeping standards and the reporting of expenditures, enrollment, acreage and count within these programs. Requiring water quality to be an explicit objective of restorations included within WIP accounting would avoid the inclusion of projects with minimal water quality benefits. Finally, we believe that research is needed on farmer attitudes in the Chesapeake Bay watershed toward wetlands for water quality protection.

Scale will be an important consideration moving forward with a targeting approach. State WIPs are developed at the county scale, but watersheds may cover multiple counties. At the scale of the entire Mid-Atlantic Coastal Plain, it may be useful to allocate efforts according to hydrogeomorphic region, with more effort to promote wetland BMPs in the "poorly drained uplands" and "surficial confined" regions. For local watersheds the size of a few thousand hectares, we believe that partnerships between government agencies, conservation planners, and researchers will facilitate engagement of landowners and selection of appropriate N management strategies. High resolution GIS data and tools will be important components of the planning process. At field scales, siting and designing wetlands with careful consideration of hydrogeomorphic controls on nitrate removal and integration of wetland BMPs into farm operations is critical.

Wetland BMPs are just one approach to addressing water quality, and must be considered in the context of the entire suite of agricultural BMPs that can be used to mitigate nonpoint source pollution. In addition to edge-of-field and off-site practices, changes in management practices to reduce N inputs will also be needed to help meet N reduction goals. By advancing our understanding of nitrate transport to potential wetlands on the coastal plain and working collaboratively with landowners, we can target areas where we expect to find the greatest benefits through wetland restoration and creation practices.

Wetlands can provide multiple ecosystem services and be an integral part of conservation programs on the Mid-Atlantic Coastal Plain. The demands of the TMDL will need to be balanced with these multiple objectives. Moving forward, we believe our proposed actions would clarify and support the use of wetland restoration and creation practices to meet water quality goals.

Chapter 3 – Digital soil disaggregation in a low-relief landscape to support wetland restoration decisions

3.1 Introduction

Knowledge of the spatial distribution of soils and soil properties is essential for understanding Earth surface processes and making scientifically-based decisions regarding the assessment, management, and monitoring of land and water resources. The field of digital soil mapping (DSM) has developed in response to the growing need for soils data and the enormous advances in remote sensing and information technology that permit rapid generation of soil property and class maps (Grunwald, 2010; McBratney et al., 2003). Digital soil mapping involves using qualitative "knowledge-based" and/or quantitative predictive models to map soil properties or classes (Bui, 2004; McBratney et al., 2003). DSM techniques commonly use legacy soils and/or field data and environmental covariates in combination with data mining and classification techniques to update soil maps (Kempen et al., 2009; Wei et al., 2010; Yang et al., 2011) or map specific soil properties (Akpa et al., 2016; Akumu et al., 2016; Odgers et al., 2014a; Rudiyanto et al., 2016). An evolving approach is to spatially disaggregate soil information within areas where multiple soil classes have been grouped together (Bui and Moran, 2001; Häring et al., 2012; Nauman et al., 2014; Nauman and Thompson, 2014; Odgers et al., 2014b; Subburayalu and Slater, 2013).

In the U.S., Soil Survey Geographic Database (SSURGO) maps consist of map unit delineations (polygons) that are comprised of multiple soil classes (components)

occurring in proportions approximated by the soil surveyors. Map units are defined and delineations are drawn at scales that reflect the purpose of the soil survey, which is generally to provide guidance on land resource management. SSURGO maps are most commonly drawn at map scales of about 1:12,000 to 1:24,000 (Soil Survey Division Staff, 1993). Disaggregation methods typically aim to create a more spatially refined representation of soil bodies by transforming the more generalized polygon-based soils map into a grid-based format where raster cells represent probabilities of belonging to individual soil component classes (series). Here, we apply the term disaggregation more broadly to include output soil categories defined based on the goals and scope of a project, rather than simply soil series. In areas where there are a large number of mapped soil series, it can be difficult to predict all series due to data imbalance and computational limitations (Subburayalu et al., 2014; Subburayalu and Slater, 2013), so it may be more useful to focus on dominant soil series or categories of interest.

Disaggregation techniques may be used to create general purpose (Odgers et al., 2014b; Yang et al., 2011) or use-specific (Thompson et al., 2010) soils maps. A potential use for disaggregated soil survey data is mapping wetlands. Wetlands are found on every continent except Antarctica and cover 4 – 6% of the Earth's surface. They provide critical ecosystem functions, including water storage, water filtration, biological productivity, and carbon sequestration (Mitsch and Gosselink, 2007). Since the 1780's, the conterminous U.S. has lost over 50% of its original wetlands (Dahl, 1990). Efforts to conserve remaining wetlands depend on routine monitoring. Wetland mapping is an essential part of monitoring wetlands to assess their function, with implications for regulation and natural resource management (Lang and McCarty, 2008). More spatially

detailed information on soils and soil properties can potentially help us better identify

areas where wetlands likely occur and understand their functions within local and

regional landscapes.

Terrain attributes derived from digital elevation models (DEMs) are among the most

commonly used predictor variables in DSM (Behrens et al., 2010a; Smith et al., 2006)

and automated wetland mapping (Kloiber et al., 2015; Lang et al., 2013; Leonard et al.,

2012). As one of Jenny's five soil forming factors, topography has a strong control on

hydrologic, erosional, and depositional processes across landscapes (Jenny, 1941;

Wysocki et al., 2011). Terrain attributes such as slope, curvature, aspect, local relief, and

topographic roughness can be used to describe geomorphic surfaces, allowing the

segregation of natural soil bodies across the soil continuum (Behrens et al., 2014; Wilson

and Gallant, 2000; Wysocki et al., 2011). Topographic wetness indices (TWIs) are useful

in mapping the potential spatial distribution of soil saturation (Beven and Kirkby, 1979),

a measure of important wetland processes (Lang et al., 2013; Rampi et al., 2014; Rodhe

and Seibert, 1999).

To date, disaggregation techniques have been applied predominantly in areas of

heterogeneous topography and geomorphology (Häring et al., 2012; Nauman et al., 2014;

Nauman and Thompson, 2014; Sun et al., 2011). Elevation data used to derive predictor

variables are typically at resolutions of 10 m or coarser. Finer resolution data with high

vertical accuracy may be needed in areas of low-relief to capture the influence of

topography on hydrology and soil forming processes. Lidar systems are active sensors

that emit short pulses of light, calculating the distance to an object by recording the

amount of time it takes for a pulse to return to the sensor. Lidar can be used to calculate

highly accurate x, y, z locations. Whereas conventional DEMs have vertical accuracies of 1-10 m, lidar-derived DEMs have vertical accuracies of 15 cm – 1 m (Lang and McCarty, 2008). Shi et al. (2012) found that terrain attributes created from 1 and 5 m horizontal resolution lidar-derived digital elevation models performed significantly better in knowledge-based digital soil mapping in a mountain watershed than 10 m National Elevation Data sources from the U.S. Geological Survey. Leonard et al. (2012) used 1 m lidar-derived DEMs with a vertical accuracy of 10 cm to generate local relief models that were able to capture subtle changes in local geomorphology important for detecting small wetlands in a low-relief area (~10 m gradient).

A popular technique used in spatial disaggregation is the decision tree model. Decision trees are machine learning algorithms that can be used for both classification and regression. Training data are passed through a series of decision rules that recursively split the data into branches at each node. Binary splits result in increasingly homogeneous subsets of the training data. Once the model has been trained with a set of known instances, it can be applied to the larger dataset to make predictions in unknown areas. Input variables can be continuous or categorical. Tree-based models show great promise for operational digital disaggregation because they are flexible, make no assumptions about the data, and are easy to interpret (McBratney et al., 2003).

A number of methods have been used to train decision tree classifiers for disaggregation models. These include: sampling polygons of legacy soil maps (Moran and Bui, 2002; Odgers et al., 2014b; Subburayalu et al., 2014), creating training areas within map unit polygons using rule matching based on legacy soils data and environmental raster covariates (Nauman and Thompson, 2014; Nauman et al., 2014), and using previously

collected soil profile data as training points (Häring et al., 2012). Sampling polygons based on relative areal extent of soil classes allows mapping large areas without field data, but the assignment of soil classes or properties to training data includes a higher level of uncertainty because polygons consist of more than one soil class. The development of rulesets to create training areas can result in high accuracy disaggregated maps in areas of heterogeneous topography where there are complete soil survey descriptions of soil geomorphic and landform attributes (Nauman et al., 2014; Nauman and Thompson, 2014). Developing soil-landscape rules in low-relief landscapes, however, is much more challenging because the topography is so subtle. Geomorphic and landform attributes may not be populated in SSURGO data tables. Thus, availability of field data is especially important in these landscapes. Where a set of representative soil profiles exists, there is opportunity to train the decision tree classifier using known instances. For example, Häring et al. (2012) used soil profile data to disaggregate complex soil map units in forests in Bavaria, Germany.

The purpose of this research was to develop a methodology for disaggregating soil survey map units for the purpose of supporting wetland restoration and conservation decisions in low-relief depressional wetland landscapes. We used a 3 m lidar bare-earth DEM with ~ 0.2 m vertical accuracy in combination with legacy soils data, the National Wetlands Inventory, and drainage ditch networks to disaggregate soil bodies within catenas that vary primarily by natural soil drainage and texture class. We derived several topographic metrics believed to reflect hydrologic and depositional processes in a low relief depressional wetland landscape. We employed the current soil landscape model for our study area to derive predictor variables from the SSURGO in an effort to better represent

soils as a continuum that reflects the parent material and soil forming processes driving variation in soil properties across the landscape. To train our disaggregation model, we used soil profile data collected from previous research and local soil surveyors.

The objectives of this research were to 1) Develop a repeatable method for spatially disaggregating soil map units to better reflect natural soil drainage and texture class in a low relief landscape; 2) Test the use of previously collected field data in training our classification model; and 3) Identify which lidar-derived topographic attributes best predict variability in soil hydrologic and depositional processes in crop and forest land within in the study area.

3.2 Materials and Methods

3.2.1 Study area

Our study area was in the upper Choptank River Watershed, which includes portions of Caroline, Queen Anne's, and Talbot Counties in Maryland and Kent County in Delaware in the Atlantic Coastal Plain of the US (Fig. 3.1). The study area is situated on the Delmarva Peninsula which is underlain by a wedge of unconsolidated sediments comprised of a surficial unconfined aquifer ranging from less than 6 meters to greater than 30 meters thick (Hamilton et al., 1993). The surficial aquifer is underlain by a series of confined aquifers (Cushing et al., 1973). Sediments of the surficial aquifer represent several time-stratigraphic units deposited in fluvial, estuarine, marine, and marginal-marine environments (Hamilton et al., 1993). The Choptank River drains the central Delmarva Peninsula in Maryland and Delaware. The 1756 km^2 watershed is relatively

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flat, with a maximum elevation of less than 30 m above sea level (Lee et al., 2000). The

region is characterized by a humid, temperate climate with average precipitation of 120

cm/yr, about half of which evaporates or is transpired by plants. The remainder recharges

groundwater or runs off into streams (Ator and Denver, 2012). Land cover in the basin

has changed dramatically over the past 350 years due to deforestation and

agriculturalization. Today, land cover in the Choptank Watershed is dominated by

agriculture (65%), with smaller amounts of forest (26%) and urban areas (6%) (Fisher et

al., 2006).
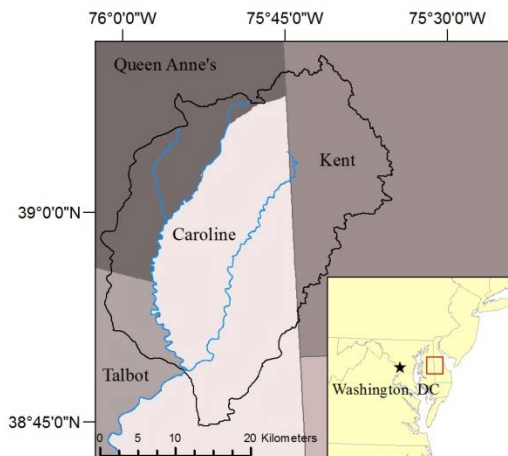
Figure 3.1 Upper Choptank River Watershed, Delmarva Peninsula.

The study was conducted in the upland areas of the Choptank Watershed, which includes

both well-drained and poorly-drained hydrogeomorphic subregions. Well-drained

uplands are characterized by well-drained soils dominated by cropland, with wooded

areas along highly incised streams. Poorly drained uplands are characterized by minimal

stream incision and the prevalence of hydric soils. Land cover in the poorly drained

subregion includes a mixture of poorly drained forest and moderately well-drained to well-drained cropland (Hamilton et al., 1993; McCarty et al., 2008). Nitrate concentrations in the Choptank basin are lower in the poorly drained uplands hydrogeomorphic region than in the well-drained uplands region, and are positively correlated with percent agriculture and negatively correlated with percent forest (Hively et al., 2011). Most of the region's wetlands are forested, including depressions, flats, and riparian wetlands (Lang et al., 2012). Forested wetland extent was once much greater prior to drainage and agricultural conversion (Lang et al., 2008).

3.2.1.1 Depressional wetlands

Depressional wetlands include Carolina bays, Delmarva bays, and other wetlands that occur in topographic depressions and exhibit a range of hydroperiods – from frequently dry to semipermanently flooded (De Steven and Lowrance, 2011). They are numerous across the Coastal Plain, but many have been lost through artificial drainage and conversion to agriculture (De Steven and Lowrance, 2011). Delmarva bays are elliptical depressions with sandy rims that occur primarily on the central portion of the Delmarva Peninsula (Stolt and Rabenhorst, 1987b). Delmarva bays and other depressional wetlands interact with surficial groundwater, and can act as both a recharge wetland in the summer and a discharge wetland in winter and spring (Phillips and Shedlock, 1993). There is great interest in the potential of these wetlands to intercept and transform agricultural nutrients and reduce sediment loads to the Chesapeake Bay, improving water quality in the Bay (Ator and Denver, 2012; Denver et al., 2014; Goldman and Needelman, 2015).

Depressional wetlands are commonly restored in the region by plugging drainage ditches, excavating topsoil, and/or building a berm.

The function and extent of depressional wetlands on the landscape is controlled largely by hydrology. Small variations in topography can have important effects on the hydrology of depressional wetlands, resulting in temporal variations in water level and soil moisture (wetland hydroperiod) that affect wetland function (Lang et al., 2013; Lang and McCarty, 2008). The ability of depressional wetlands to store carbon, for example, is related to anaerobic conditions created by high water tables and prolonged soil saturation (Fenstermacher et al., 2016, 2014).

3.2.1.2 Local soil survey

The most recent soil survey was completed in 1995 in Queen Anne's county and 2009 in Caroline and Talbot counties. These soil maps and data are available through the Soil Survey Geographic database (SSURGO) on Web Soil Survey, a website maintained by the United States Department of Agriculture Natural Resources Conservation Service (Soil Survey Staff, 2014). SSURGO data consist of polygons representing map units and tabular soil property data associated with distinct components within each map unit. A single SSURGO map unit may contain several major and minor components, each associated with different soils with contrasting properties.

The expert-derived mapping model for the study area was based on distinguishing groups of soils primarily based on particle-size family class and surface texture (Appendix A, Supp. Table 3.1). Within groups, soils were differentiated by depth to water table as

indicated by hydromorphic features, including depth to iron depletions, depth to gleyed

horizons, and surface organic matter accumulation and thickness. For example, the fine-

loamy group consists of Sassafras (water table depth > 180 cm), Hambrook (100–180

cm), Woodstown (50–100 cm), Marshyhope (25–50 cm), Fallsington (0–25 cm), and

Corsica (ponded to 0 cm) (Fig. 3.2). Soils within groups were commonly mapped

adjacent to one another, although pockets of high clay soils (Lenni series) occur in

sandier areas, and soils on rims of depressions may be coarser textured than those in

centers of depressions. Map unit polygons were delineated using topographic maps and

color infrared imagery.
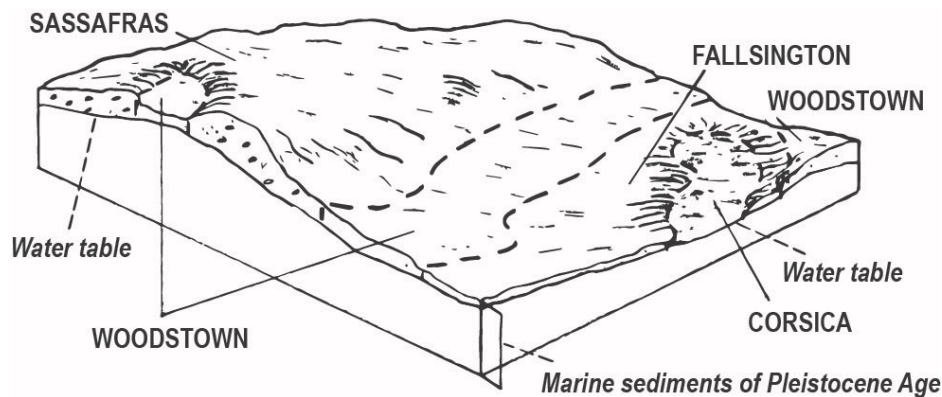
Figure 3.2 Block diagram showing relationship of soils to topography and water table in depressional wetland landscapes on Delmarva Peninsula, Maryland (*adapted from Soil Survey Staff (1970)*).

All but one map unit within the study area were mapped as consociations, which are

comprised of one dominant component plus minor components. The remaining map unit

was a complex mapped in Caroline County – the Hammonton-Fallsington-Corsica

complex, which was extensively mapped in areas containing Delmarva bay landforms in forested areas. This complex was used in these areas both to represent the fine-resolution catena associated with Delmarva bays and due to limited access to these areas, which made identification of individual consociations difficult. The SSURGO maps are thought to be less accurate in forested areas relative to agricultural areas, where more extensive field data were collected and less vegetation would have made it easier to interpret color infrared imagery (i.e., saturated soils would have been easier to identify on cropland because the soil would have had little or no vegetation cover when images were collected).

3.2.2 Study design

To develop the disaggregation model, we followed procedures similar to those described by Nauman et al. (2014) adapting them to meet our project goals and fit local landscape characteristics. First we selected our map units and defined our soil classes. Next we assembled our environmental covariates. As our focus was on the hydrologic properties of soils, we created several topographic metrics expected to have the greatest influence on soil hydrology and erosional/depositional processes in this low-relief depressional wetland landscape: local elevation, specific catchment area, topographic wetness index (TWI), a 'sink' index indicating the likelihood a raster cell has no surface outlet, midslope position, and the morphometric protection index (MPI) (Table 3.1). Primary metrics such as slope and curvature were not included because initial observation of these surfaces indicated that they did not describe depressional landforms as well as the other metrics.

Topographic metrics were developed using a DEM derived from lidar data collected in spring 2006 (vertical accuracy ~ 0.2 m). Since the data were collected in spring when inundation is highest, the bare earth lidar data used to create the DEM may not accurately reflect the surface in inundated areas. This is due to the absorption of incident near infrared energy by water. Ideally, lidar data used to derive elevation models in the region would be collected in November-December, when inundation is lowest. These were the only lidar data available at the time, however.

The 2 m DEM was resampled to 3 m using cubic convolution and projected using the Universal Transverse Mercator projection (zone 18N, North American Datum 1983) in ArcMap 10.2 (Esri, 2011). Three meters was selected for the resolution of the study to provide the degree of detail that would be appropriate for distinguishing soil bodies in this landscape. Other attributes were derived from SSURGO, the National Wetlands Inventory (NWI) and the agricultural ditch network (discussed below). Pedon data were assembled from existing field data for training our model. We then went through several iterations of model building and soil map generation until we were satisfied with our predictions. Finally, we an independent field validation of the disaggregation model was conducted. Steps are described in more detail below.

Table 3.1 Environmental covariates derived from Soil Survey Geographic Database (SSURGO), National Wetlands Inventory (NWI), and 3m lidar digital elevation models used in Random Forest models in the upper Choptank River Watershed, Maryland and Delaware.

Variable	Abbreviation	Description	Models
SSURGO Map Units	MU	Grouped according to natural drainage class and texture class.	forest, crop
Adjacent SSURGO map units	ADJ MU	Map unit group with the highest percent area in a 200 m radius.	forest, crop
Topographic Wetness Index	TWI	SAGA wetness index. Based on slope and contributing area calculated using a multiple flow direction algorithm.	forest, crop
Catchment Area	CA	Modified Catchment Area in SAGA: Upslope contributing area per unit contour length.	forest, crop
Morphologic Protection Index	MPI	Topographic openness. Expresses the dominance or enclosure of a landscape location.	forest, crop
Local Elevation	LELEV	Deviation from mean elevation. Difference from the mean elevation in a 200 m radius divided by the standard deviation.	forest, crop
Mid-Slope Position	MIDSL	The extent that a location is similar to a ridge or valley position.	forest, crop
Sink Index	SINK	A measure of how likely a raster cell is a sink or an area of undefined flow direction.	forest, crop
NWI water regime	NWI	The National Wetlands Inventory water regime modifier	forest
Ditch density	DIT DEN	Density of agricultural ditches in a 200 meter radius	crop
Ditch distance	DIT DIS	Distance to an agricultural ditch	crop

3.2.2.1 Map unit selection

Separate disaggregation models were built for forested and agricultural areas due to the

differences in SSURGO mapping between these areas and because of extensive ditching

and subsurface drainage in agricultural areas. Because there are over 100 soil series

developed in similar parent material mapped in the study area, we decided to limit the

number of soil classes we would try to predict in order to focus on differentiating natural

soil drainage class and particle-size family class. Soil series were therefore grouped according to the NRCS soil mapping model as described in Supplemental Table 1. Combinations of natural soil drainage class and particle-size family class yielded 20 soil groups (5 natural soil drainage classes: very poorly, poorly, somewhat poorly, moderately well, and well drained; and 4 particle-size family classes: fine, fine-silty/fine-loamy, coarse-loamy, and sandy). Fine-loamy and fine-silty were combined since sand and silt percentages were not recorded in the field-based training data. Examination of our training data and covariate surfaces and initial model runs indicated the model would not be able to differentiate such a large number of soil groups, and so we decided to model drainage class and texture class separately. Natural soil drainage class of each training point was assigned by applying strict criteria based on depth to redox features and thickness and darkness of the A horizon. When mapping, however, the soil surveyor may also consider ancillary information in determining drainage class (discussed below).

3.2.2.2 Assembly of environmental covariates

3.2.2.2.2 Ditch network attributes and removal

Since an extensive ditch network covers much of the cropland in the region, we filled the ditches in order to create smooth surfaces for deriving the topographic metrics. The 3 m DEM was exported to an ASCII file to be filtered using System for Automated Geoscientific Analyses (SAGA) v. 2.2.2, a free open-source software designed for the analysis of spatial data (Conrad et al., 2015). An edge filter was applied to the DEM using a 3x3 cell neighborhood. We then classified the filtered DEM in ArcMap using

Jenks natural breaks and selected grid cells corresponding to ditches. Ditch cells were assigned a value of 1 and all other cells a value of 0. We used the raster cleanup tool to remove erroneous cells from the ditch network and then vectorized the raster to create a vector ditch layer in ArcScan (Esri, 2011).The vector ditch layer was further refined using editing tools in ArcMap and then used to derive our ditch attributes (see below). To fill the ditches we applied a 12 m buffer and removed the buffered cells from the unfiltered DEM. We then filled the buffered ditches with the mean cell value in a 5x5 cell neighborhood. The filled ditches were smoothed using a 5 kernel mean filter applied twice. Major roads were smoothed using similar methods (15 m buffer and 7 kernel mean filter).

The presence of ditches is often an indication that soils were originally too wet to farm, and thus we expected more very poorly to somewhat poorly drained soils near ditches. We derived two attributes from the ditch network: ditch distance (DIT DIS) and ditch density (DIT DEN). Ditch distance was calculated using the Euclidean distance tool and ditch density using the line density tool with a 200 m radius in Spatial Analyst (Esri, 2011). The ditch density layer was filtered several times with increasing kernel sizes in order to remove abrupt changes and create a smooth surface (Fig. 3.3).
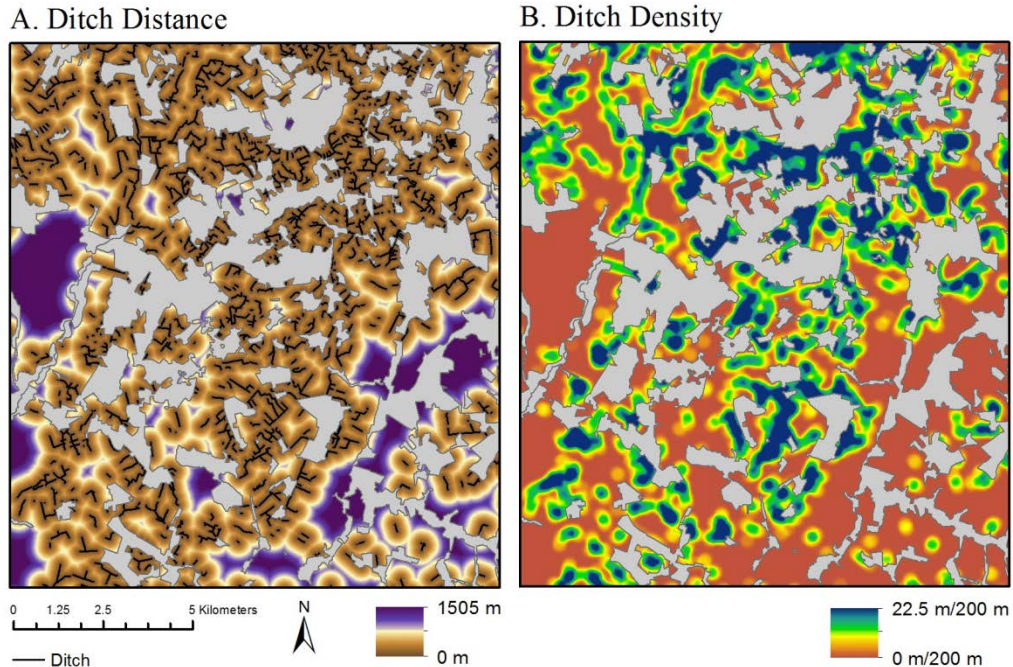
Figure 3.3 Random Forests covariates derived from digitized drainage ditch layer in the upper Choptank River Watershed, Maryland and Delaware. Gray areas are forested.

3.2.2.2.3 Topographic attributes

Local elevation (LELEV)

As our local elevation metric, we chose to use the deviation from mean elevation which measures the relative topographic position as a fraction of local relief (Wilson and Gallant, 2000) (Fig. 3.4). We first calculated the mean and standard deviation of the unfiltered DEM in a 200-m radius. This neighborhood size was chosen based on previous work on topographic metrics conducted by Lang et al. (2013) in the study area. We then filtered the DEM twice in SAGA using a 3 kernel low pass filter and calculated relative elevation as:

$$(\text{filtered DEM} - \text{mean elevation}) / \text{standard deviation}$$

Midslope position (MIDSL)

Midslope position was calculated using the Relative Heights and Slope Positions module in SAGA v. 2.2.2 (Böhner and Selige, 2006). Midslope position calculates the extent that each cell is similar to a ridge or a valley position, with values on a scale of 0-1. The 3 m DEM was filtered twice with a 3 kernel and once with a 9 kernel low pass filter before running the module (Fig 3.4).

Specific catchment area (CA) and topographic wetness index (TWI)

Specific catchment area (upslope contributing area per unit contour length) and TWI were calculated using SAGA v. 2.0.8. The SAGA Wetness Index module (Böhner et al., 2001; Böhner and Selige, 2006) calculates TWI using a multiple flow routing algorithm based on slope (Freeman, 1991). The 3 m DEM was filtered twice with a 3 kernel and once with a 9 kernel low pass filter before running the module (Fig 3.4).
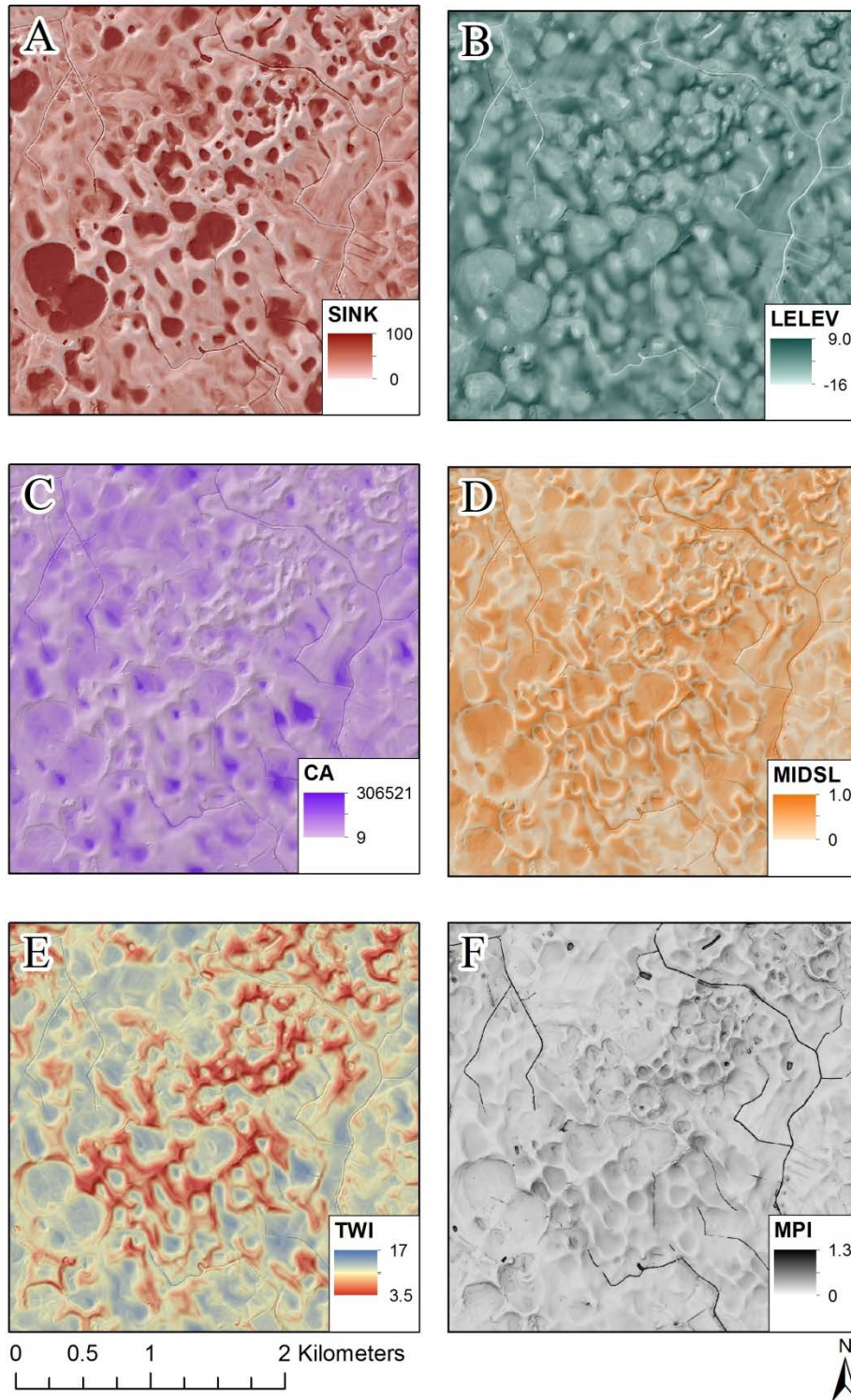
Figure 3.4 Topographic covariates derived from 3 m lidar digital elevation models used in Random Forests models in the upper Choptank River Watershed, Maryland and Delaware: A) Sink Index; B) Local Elevation Index; C) Catchment Area; D) Midslope Position; E) Topographic Wetness Index; F) Morphometric Protection Index.

Morphometric Protection Index (MPI)

MPI is a measure of topographic openness that expresses the dominance or enclosure of a location in the landscape (Yokoyama et al., 2002). The MPI was included as a potential indicator of depositional and erosional processes on wetland depressions, which could be predictive of soil texture. To calculate MPI, the unfiltered DEM was filtered three times using a multi direction Lee filter prior to running the MPI module in SAGA (Fig. 3.4).

Sink index (SINK)

We used ArcGIS Model Builder to calculate the sink index on the Lee-filtered DEM following methods similar to those described in Wu et al. (2014) (ESRI, 2011). Using the lidar data root mean squared error (0.2 m) to represent the magnitude of error in the elevation data, a Gaussian probability function (mean = 0, standard deviation = 0.2 m) was used to create a distribution of the probability of lidar error. A simulation was then run in which a random sample was drawn from the probability function and added to each grid cell in the original DEM, and the cells in the error-added DEM were filled using the Fill tool in Spatial Analyst. With each iteration, filled cells were added to a cumulative grid. One hundred iterations were run and the resulting cumulative grid was used to represent the probability that a given cell belonged to a depression feature (Wu et al., 2014). Cell values in the sink index surface ranged from 0 to 100, with higher values indicating a cell was likely in a depression (Fig. 3.4).

3.2.2.2.4 SSURGO-derived attributes

Two predictor variables were created from the SSURGO maps (Fig. 5). The first surface

(MU) was developed by grouping the SSURGO map units according to the natural soil

drainage and particle-size family classes (Fig. 3.5a). The second surface (ADJ MU) was

derived from the first by determining which map unit groups covered the greatest areal

extent within a 200 m radius of each raster cell (Fig. 3.5b). This second surface was

intended to provide a measure of spatial relationships among soil classes by incorporating

soil information from the local area. By considering soils adjacent to the cell being

predicted, we sought to better represent soil systems – distinct groups of recurring soil

sequences that are a product of stratigraphy, geomorphology, hydrology, and climate

(Daniels, 1984).
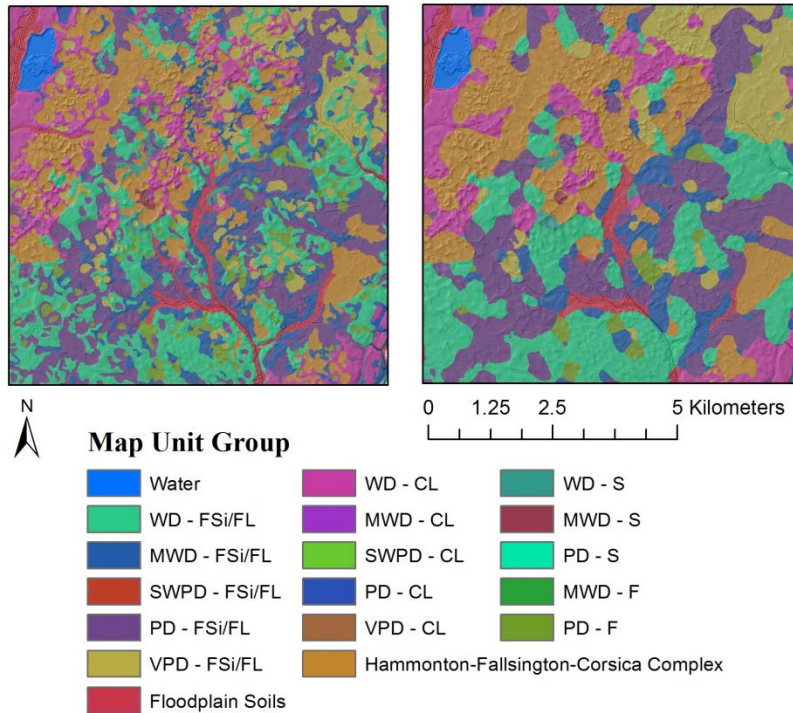
Figure 3.5 Random Forests covariates derived from Soil Survey Geographic Database (SSURGO) map units. Map units were grouped according to the Natural Resources Conservation Service mapping model for Caroline County, Maryland (Appendix A, Supp. Table 3.1). *Left*: Map unit group (MU); *Right*: dominant map unit group within 200 m radius of each raster pixel (ADJ MU). WD = well drained; MWD = moderately well drained; SWPD = somewhat poorly drained; PD = poorly drained; VPD = very poorly drained; FSi/FL = fine silty/fine loamy; CL = coarse loamy; S = sandy; F = fine.

3.2.2.2.5 National Wetlands Inventory (NWI)

Hydrologic modifiers from the NWI dataset were used to derive a wetlands layer for forested areas. Raster cells were classified into a total of 24 categories describing frequency and degree of saturation and flooding.

3.2.3 Training data

Training data were derived from 382 pedon descriptions collected during NRCS soil survey, previous field research (Fenstermacher, 2012; Palardy, in prep) and this study. The NRCS pedon descriptions were collected during survey updates in the 1990s and 2000s. Since no GPS coordinates were recorded at the time of the survey updates, locations of Soil Survey pedons were estimated based on handwritten notes included with the descriptions. Approximate locations of pedons were indicated by labeled points on color infrared aerial photographs. Points were digitized in ArcMap 10.2 (Esri, 2011) using background imagery as a reference. NRCS pedon descriptions were of soil series that tend to form on depressions (centers, slopes, and rims), but not all points were located on depressions. The research pedons were described in studies on carbon storage and decomposition in depressional wetlands in the Choptank watershed and included GPS coordinates (Fenstermacher, 2012; Fenstermacher et al., 2016; Palardy, in prep). Prior to building our model we collected 22 pedon descriptions with NRCS survey staff during preliminary investigations of forested wetlands in the study area. We then went through each of the 382 descriptions and omitted all of those that did not fall within the study area. Also, in consultation with the NRCS, a small number of pedons were omitted because they exhibited unusual characteristics that made them difficult to classify based solely on the pedon descriptions. A total of 293 pedons were selected to train separate ensemble decision tree classifiers for forested areas and cropland.

3.2.4 Modeling

Random Forests is an ensemble tree model in which each tree in the ensemble is built from a sample drawn with replacement from a training set (Breiman, 2001). A random selection of predictor variables is used to split the data at each node in the tree. The probability that an individual raster cell belongs to a particular soil class is based on the percentage of trees in the ensemble that predict that class for that cell. Random Forests are robust to Random Forests have been used to disaggregate soil components in West Virginia and Arizona landscapes (Nauman et al., 2014; Nauman and Thompson, 2014). Random Forests were also used by Häring et al. (2012) to spatially refine soil classes in complex map units and by Heung et al. (2014) to map soil parent material.

R statistical software was used to build our Random Forests decision tree classifiers (Breiman, 2001; Liaw and Wiener, 2002; R Core Team, 2014). Our training points were divided into 98 forest points and 195 cropland points. In Random Forests, approximately one-third of the training data are left out when a bootstrap sample is drawn from the training set to build each tree. These out-of-bag (OOB) data are used to calculate an unbiased estimate of the classification error as trees are added to the forest. After each tree is created, both the training and OOB data are run down the tree. If two cases fall in the same terminal node, their proximity is increased by one. Proximities are normalized by dividing by the number of trees. Proximities can be used to identify outliers (cases whose proximities to all other cases are small) and visualize the data using metric scaling (Breiman, 2001). Using the proximity measure and the training classification error rates for each soil class in each model, we identified and removed outliers and combined soil classes. Classes were largely imbalanced in both cropland and forest areas, with very

poorly drained soils making up the majority of forest training points, and well drained soils the majority of cropland training points. Soil classes were combined into three drainage groups (very poorly/poorly, somewhat poorly/moderately well, and well drained) and two texture groups (fine and coarse) for forested areas and four drainage groups (very poorly, poorly, somewhat poorly/moderately well, and well drained) and two texture groups (fine and coarse) for cropland. Soils categorized as fine included those with fine-loamy, fine-silty and fine particle size classes (> 18% clay) according to Soil Taxonomy (Soil Survey Staff, 2010). Soils categorized as coarse included those with coarse-loamy or sandy particle size classes (< 18% clay) (Appendix A, Supp. Table 3.1). Three outliers were identified and removed from the forest training set in the drainage group model. Two hundred trees were used to grow each Random Forests model.

3.2.5 Field validation

Predictions were validated with independent field data collected from 24 forested wetlands and 24 wetlands converted to agriculture at a total of 12 field sites (6 forest, 6 cropland). Sites were selected based on accessibility and to maximize distribution within the study area. Within each site, three depressional wetlands were selected at random for sampling within the set of accessible depressions at the given site.

At each depressional wetland, transects were run from the center to the rim. We used a stratified random design to sample pedons within the depression, along the slope, and on the rim. The direction of each transect was selected using a random number generated based on degrees from North. Distances along each transect from the edge of each zone

were selected randomly for sampling. Two samples were collected within depressions, one along the slope, and one on the rim. In forested areas, samples within depressions were stratified based on presence/absence of standing water. On cropland, one sample was taken within 10 steps of the center of the depression and one between 10 steps and the edge of the depression. A total of 142 descriptions were collected (only one depression sample was taken at two of the forested wetlands) (Appendix B).

3.3 Results and Discussion

3.3.1 Model training

Random Forests models were better able to capture differences in both drainage and texture groups in forested areas than in cropland. In forested areas, overall training error in the drainage group classification was 9.5%, with the majority of misclassified points in the well-drained group (Table 3.2). Training error in the forest model was 39.8% for the texture group classification (Table 3.3). On cropland, drainage group training error was 28.7% when SSURGO attributes were included and 23.6% when SSURGO attributes were omitted (Table 3.4). Texture group training error was 25 – 26% on cropland, but coarse textured soils appeared to be highly underrepresented due to training class imbalance (74% fine, 26% coarse). Results of the cropland texture model are included in supplemental materials (Appendix A – Supp. Tables 3.2 & 3.3, Supp. Figures 3.1 & 3.2).

Table 3.2 Training point accuracy of drainage group predictions by Random Forests models in forested areas in the upper Choptank River Watershed, Maryland and Delaware; overall training accuracy 90.5%.

	Reference		
	VPD/PD	SWPD/MWD	WD
VPD/PD	66	2	1
SWPD/MWD	0	16	5
WD	0	1	4
Class error	0.0	0.16	0.60

Table 3.3 Training point accuracy of texture group predictions by Random Forests models in forested areas in the upper Choptank River Watershed, Maryland and Delaware; overall training accuracy 60.2%.

	Reference	
	Coarse	Fine
Coarse	44	22
Fine	17	15
Class error	0.28	0.59

There are several possible explanations as to why we had better results in forest than on

cropland. The majority of our training data on cropland came from handwritten notes

taken by the soil surveyor. No GPS coordinates were collected at the time, so locations

were approximated by the surveyor and then approximated by us when we digitized the

points in a GIS, likely resulting in poor location accuracy compared to the GPS located

pedons collected in forested areas. Furthermore, these areas have been farmed since the

1600s, with intensive agricultural practices for the past 60 years. Erosion, deposition and

mixing of the top 30 inches of the soil have likely changed the topography, modified soil

textures, destroyed redox features, and depleted soil carbon. Installed ditches and

subsurface drainage have drawn down the water table as well, resulting in carbon

depletion. Although we tried to compensate for some of these alterations by filling the

drainage ditches in our DEM to mimic the landscape under which these soils originally

developed, depth to redoximorphic features and thickness/darkness of the A horizon may

no longer be well correlated with topography. Additional non-topographic indicators are

therefore needed to identify seasonal fluctuations in the water table and locate potential

areas for wetland restoration.

Table 3.4 Training point accuracy of drainage group predictions by Random Forests models in cropland areas in the upper Choptank River Watershed, Maryland and Delaware: a) With map unit covariates (overall training accuracy 71.3%); b) Without map unit covariates (overall training accuracy 76.4%).

(a)

	Reference			
	VPD	PD	SWPD/MWD	WD
VPD	25	11	0	0
PD	17	38	6	2
SWPD/MWD	0	1	0	2
WD	2	2	13	76
Class error	0.43	0.27	1	0.05

(b)

	Reference			
	VPD	PD	SWPD/MWD	WD
VPD	30	7	0	0
PD	11	42	6	3
SWPD/MWD	1	2	2	2
WD	2	1	11	75
Class error	0.32	0.19	0.89	0.06

3.3.2 Attribute importance

3.3.2.1 Forest

We evaluated attribute importance based on the permutation importance measure output of the Random Forests model. Permutation importance measures the mean decrease in classification accuracy on the OOB samples when a particular variable is excluded from the model. For forested areas, SINK was the best predictor of drainage group, with LELEV, CA, and TWI following (Fig. 3.6a). LELEV and CA were the best predictors of texture group in forested areas (Fig. 3.6b).

SSURGO attributes and the NWI water regime were not top predictors for either drainage or texture group. Forested areas with many topographic depressions were largely mapped as complexes (Table 3.5), so SSURGO's ability to differentiate soil drainage and texture groups is greatly limited in these areas. Part of the reason NWI was not an effective predictor on forest land may be that there were a large number of NWI water regime classes with few training instances of each class. In addition many depressions are smaller than the NWI minimum mapping unit of 0.5 acres and thus may not be included in the dataset. Finally, forested wetlands are known to be particularly challenging to map using NWI techniques (Tiner, 1990).

Forest - Drainage Group

Forest - Texture Group
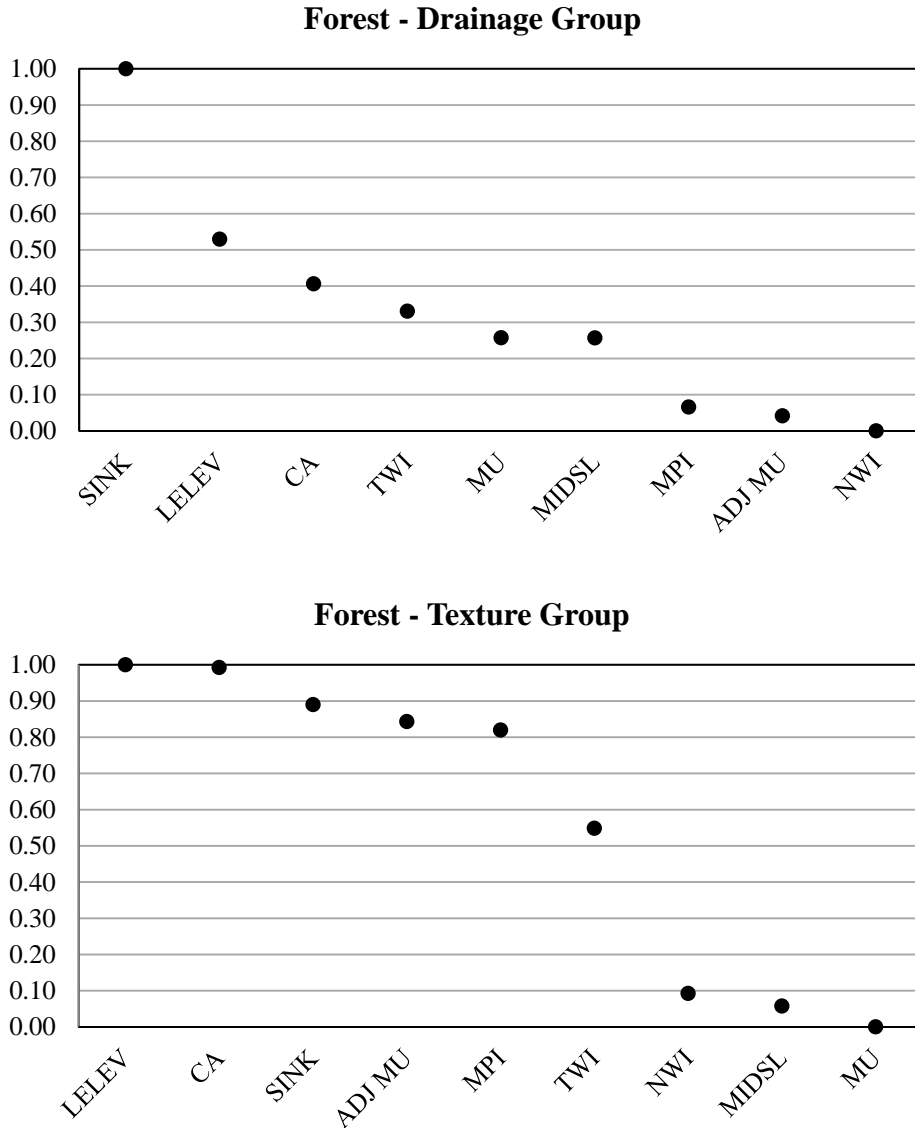
Figure 3.6 Relative importance of Random Forests variables in predicting (a) drainage group and (b) texture group in forested areas in the upper Choptank River Watershed, Maryland and Delaware. SINK = Sink Index; LELEV = Local Elevation Index; CA = Catchment Area; TWI = Topographic Wetness Index; MIDSL = Midslope Position; MPI = Morphometric Protection Index; MU = SSURGO Map Unit Group; ADJ MU = Dominant SSURGO Map Unit Group in 200m radius; NWI = National Wetlands Inventory water regime modifier.

Table 3.5 Hammonton-Fallsington-Corsica complex in Caroline County, Maryland.

HoB Complex Component (%)	Natural soil drainage class	Particle-size class
Hammonton (35%)	MWD	CL
Fallsington, undrained (20%)	PD	FL
Fallsington, drained (10%)	PD	FL
Corsica, undrained (15%)	VPD	FL
Corsica, drained (5%)	VPD	FL
Minor components (15%)	PD (3%), WD (12%)	CL (10%), S (2%), Fi (3%)

Attribute importance can help us understand topographic controls on hydrology and erosion/depositional processes in forested depressional wetlands. Previous research in this area by Lang et al. (2013) indicates that extent and location of inundation in drier years is largely controlled by the surface expression of groundwater, whereas during wetter years surface water flows are also an important control of inundation extent and distribution. Local relief, a measure of the land surface relative to the groundwater table (similar to LELEV), was an important predictor of inundation in dry years, whereas TWI was a better predictor of inundation in wet years. The sink index, a measure of surface water outlets, was the best predictor of soil drainage groups in our study, indicating that the lack of an outlet for water is important for the formation of redoximorphic features in these depressions.

Depressional landforms are characterized by sandy rims, with finer textured soils often found within depressions. This trend is captured by the Hammonton-Fallsington-Corsica complex, comprised of moderately well drained Hammonton soils with coarse-loamy

textures and more poorly drained Fallsington and Corsica soils with fine-loamy textures. Often, a silty basin fill is present in the centers of depressions, which is thought to be loess that was deposited during the last glacial period and relocated to the centers of depressions by erosion and deposition (Stolt and Rabenhorst 1987). The finding that LELEV and CA were the best predictors of soil texture group in forested areas is therefore consistent with the soil mapping model. Finer materials are expected to occur in local low spots, and larger catchment areas would contribute more fine materials to these low spots.

We were not able to distinguish very poorly from poorly drained soils in forested areas. In preliminary runs of our model, nearly all poorly drained soils were classified as very poorly drained soils. Sometimes adjustment of model parameters and class weighting can improve classification in Random Forests models, but we did not see any improvement when we made adjustments to our model. It is possible that the topographic metrics were not able to distinguish these classes because there is not enough variation in surface characteristics within depressions, thereby limiting their predictive power. The addition of other types of remotely sensed data could aid in distinguishing these soil drainage classes within forested areas. Remote sensing data that have successfully been used to map hydrologic characteristics of forested depressional wetlands in the region include multitemporal C-band synthetic aperture radar (SAR) (Lang et al., 2008), lidar intensity data (Huang et al., 2014; Lang and McCarty, 2009), and Landsat time-series imagery (Huang et al., 2014; Jin et al., 2017).

3.3.2.2 Cropland

On cropland, when SSURGO attributes were included, MU was the most important

predictor of drainage group, followed by LELEV (Fig. 3.8). When SSURGO attributes

were not included, LELEV was the most important predictor. In informal sensitivity

analyses conducted while developing our Random Forests model involving varying

model parameters, removing attributes, and weighting classes, we noticed considerable

variability in the ranking of the other attributes. LELEV was regularly a top predictor of

drainage group, however, which is consistent with the soil surveyor's mental model of

the soil landscape, and may help explain differences in hydrologic controls in forest vs.

cropland. In agricultural areas, proximity to the water table may be more important than

the lack of surface water outlets for controlling frequency and duration of soil saturation

and inundation. Drainage ditches were installed to lower the water table so these areas

could be farmed.

Crop - Drainage Group - With Map Units

Crop - Drainage Group - Without Map Units
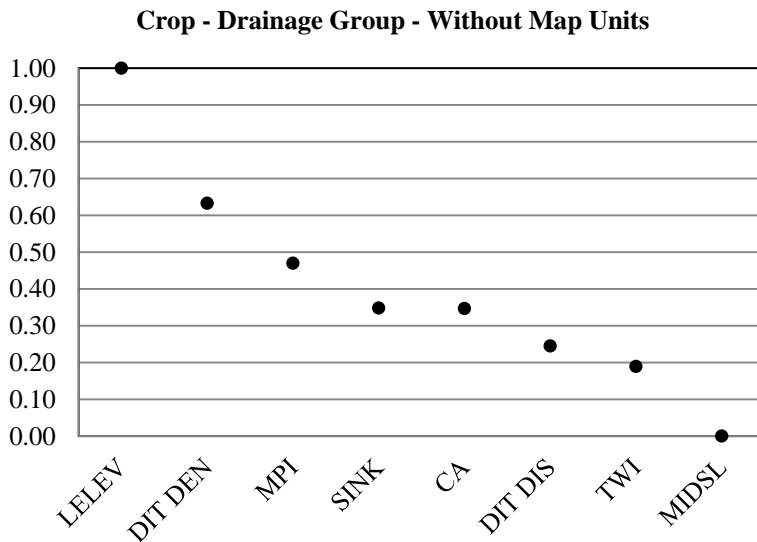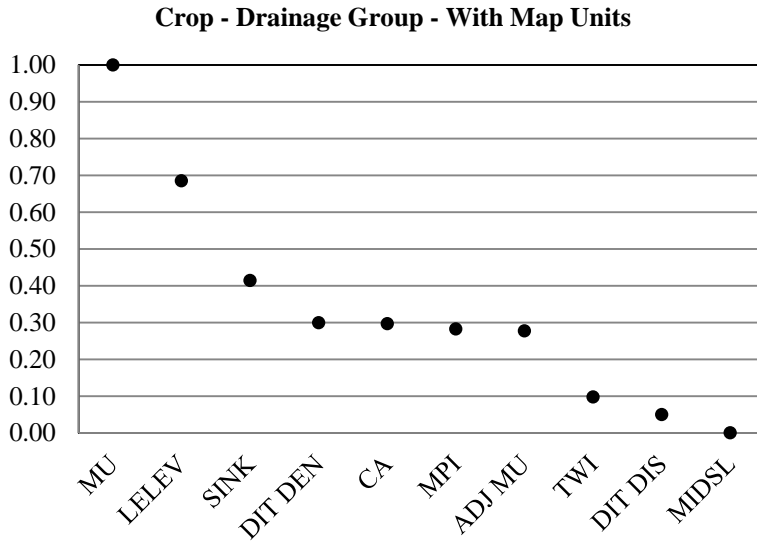
Figure 3.7 Relative importance of Random Forests variables in predicting drainage group in cropland areas in the upper Choptank River Watershed, Maryland and Delaware. SINK = Sink Index; LELEV = Local Elevation Index; CA = Catchment Area; TWI = Topographic Wetness Index; MIDSL = Midslope Position; MPI = Morphometric Protection Index; MU = SSURGO Map Unit Group; ADJ MU = Dominant SSURGO Map Unit Group in 200m radius; NWI = National Wetlands Inventory water regime modifier; DIT DEN = Ditch density; DIT DIS = Distance to ditch.

3.3.3 Soil probability maps

Probability maps for the forest models showed the highest likelihood of very poorly and poorly drained soils within depressions, somewhat poorly and moderately well drained on slopes, and well drained soils on rims (Figure 3.8). Coarse soils were predicted to occur
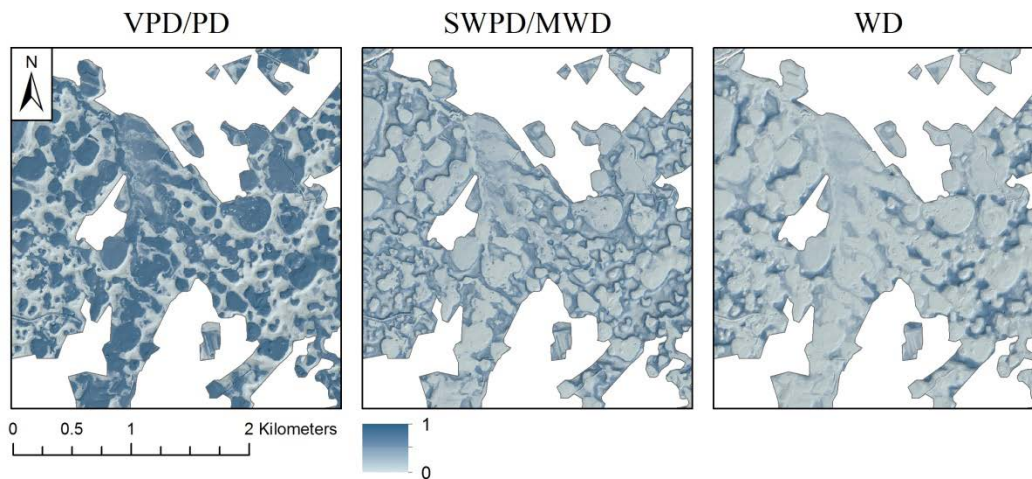
Figure 3.8 Probability of each drainage group predicted by Random Forests model in forest areas in the upper Choptank River Watershed, Maryland and Delaware.

on rims and slopes and finer textured soils in depressions (Figure 3.9). Compared to the original SSURGO maps, the model-generated maps capture more landscape detail, highlighting individual depressions and their rims (Figures 3.9 & 3.10). Much of the forest in our study area was mapped as the Hammonton-Fallsington-Corsica complex, which includes very poorly to well drained components (Table 3.5). SSURGO data are commonly mapped as dominant condition when used as input in hydrologic and other environmental models; that is, for each map unit like soil classes are grouped, their corresponding percent compositions are summed, and the class with the largest percent

composition is assigned to the map unit (Soil Survey Staff, 2014). When mapped as the

dominant condition, the Hammonton-Fallsington-Corsica complexes are mapped as

moderately well drained. However, the probability maps suggest that there are higher

percentages of very poorly to poorly drained and well drained soils in these forested

areas. Moderately well drained soils are likely confined mainly to slopes of depressions.
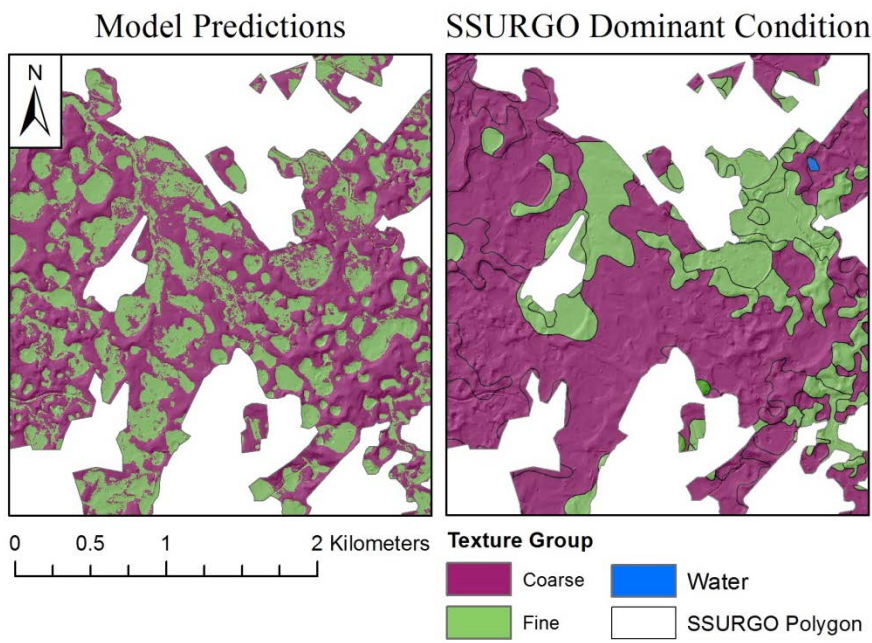
Figure 3.9 Soil texture group predictions and Soil Survey Geographic Database (SSURGO) particle size class in forest areas upper Choptank River Watershed, Maryland and Delaware. Fine include fine-loamy, fine-silty, and fine particle size classes. Coarse include coarse-loamy and sandy particle size classes.
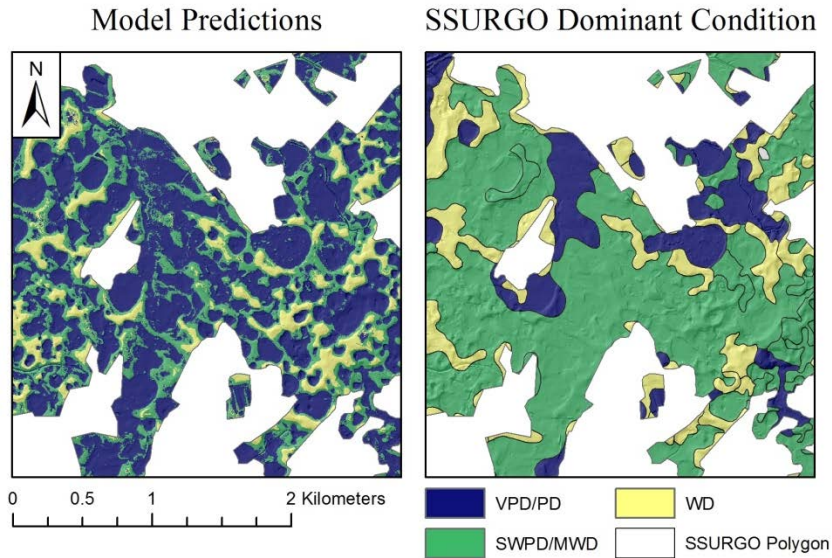
Figure 3.10 Soil drainage group predictions and Soil Survey Geographic Database (SSURGO) drainage class in forest areas in the upper Choptank River Watershed, Maryland and Delaware.

In the cropland model, when SSURGO attributes were included, transitions between predicted drainage groups closely followed SSURGO delineations, but predicted drainage group did not always match SSURGO (Figure 3.11), particularly with the SWPD/MWD soils, which were not as well represented in the training set as the other drainage groups. Most of the area mapped as SWPD/MWD by SSURGO (including Woodstown and HoB complexes) was mapped as other drainage groups by the model; this was also the case when SSURGO attributes were omitted from the model. In both cropland models, transitions between PD and VPD soils did not always follow the expected drainage pattern; in some depressions, VPD soils were mapped along the edges of depressions and PD soils in the center (Appendix A, Supp. Figure 3.3). One possible explanation for this is the presence of pockets of poorly drained high clay Lenni soils throughout the region. Lenni soils occur in depressions as dominant components in consociations and as minor

components in Hammonton-Fallsington-Corsica complexes. The training data included 35 points classified as Lenni or "Lenni-like," most of which were in centers of depressions and classified as PD according to the criteria used in our model. Another possible explanation is extensive modification of the terrain making it difficult for the model to differentiate neighboring soil classes in low relief areas. The use of crisp soil classes can lead to poor results if there is considerable overlap in the feature space (Hengl et al., 2007).

One way to address the challenge of defining target soil classes in DSM would be to use fuzzy membership classes instead of crisp classes. For example, Hengl et al. (2007) found that the use of fuzzy membership classes improved interpolation of soil categorical variables when using soil profile observations to produce soil class maps in Iran. Yang et al. (2011) used fuzzy membership classes to update conventional soil maps in Canada, resulting in DSM maps with much greater spatial detail and higher accuracy than conventional maps.
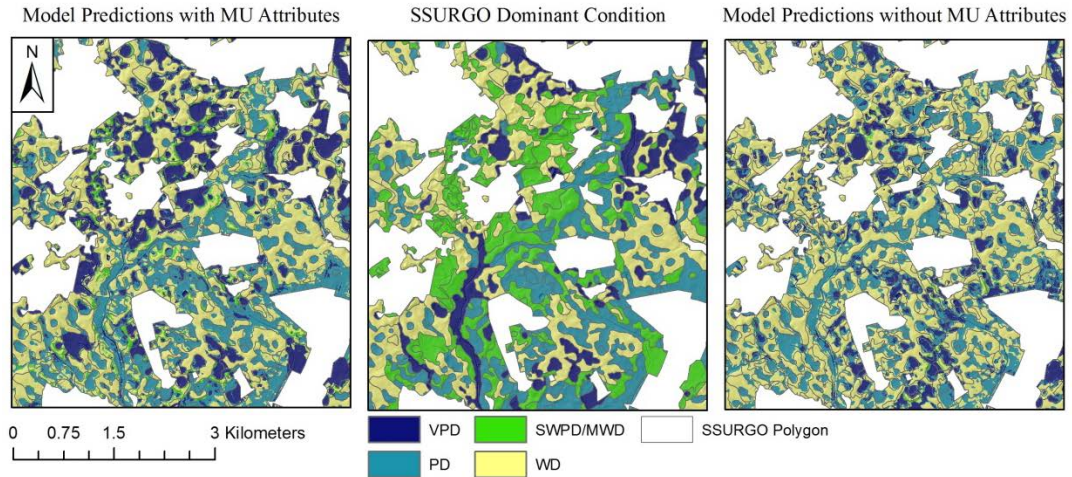
Figure 3.11 Soil drainage group predictions and Soil Survey Geographic Database (SSURGO) soil drainage class (dominant condition) in cropland areas in the upper Choptank River Watershed, Maryland and Delaware.

3.3.4 Class confusion indices

To identify where our models had the greatest difficulty distinguishing drainage and texture groups, we developed a class confusion index (CI) from our probability maps using the following equation from Odgers et al. (2014b):

$$CI = 1 - (P_{max} - P_{max-1})$$

where P_{max} is the probability of the most probable soil class and P_{max-1} is the probability of the second most probable soil class. The CI is a measure of the model's ability to assign the 'correct' class to each raster pixel. If the difference in the probabilities of the most probable and second most probable classes is small, than the CI is higher, indicating the model is more 'confused' as to which is the correct class. If the difference is large, than the CI is small, indicating the model is more confident in its assignment.

In forest areas, both drainage and texture models had the greatest difficulty distinguishing soil group on slopes of depressions, particularly on the lower slopes of depressions for the texture model (Figure 3.12). The models showed high confidence in their predictions in centers of depressions and on rims in most of the study area. On cropland, predictions of drainage group showed much higher levels of uncertainty than predictions of drainage group in forest areas (Figure 3.13). When SSURGO attributes were included, the CI tended to follow map unit delineations, with sharp changes in the index along polygon edges, indicating the model may be overfitting to SSURGO. The CI tended to be much lower in well drained SSURGO polygons than in polygons in other drainage classes. When SSURGO attributes were not included, patterns in the CI were more similar to those in forest areas, with high CI along slopes of depressions.
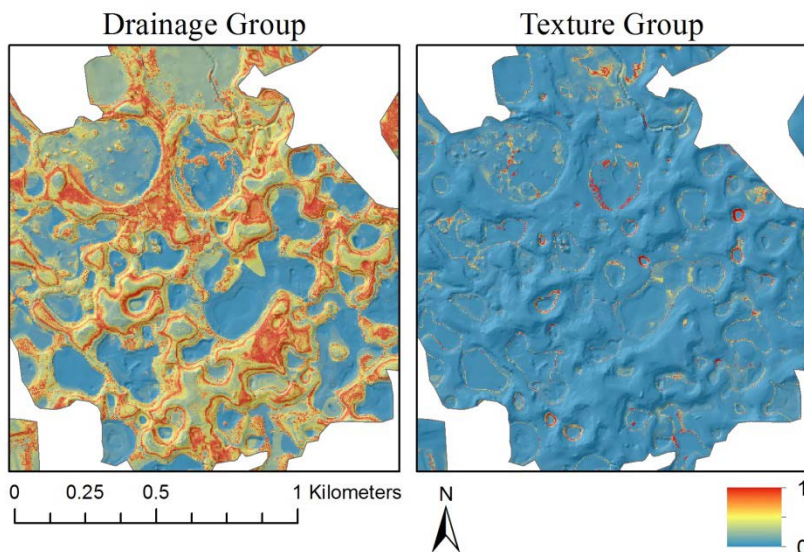
Figure 3.12 Confusion between the most probable and second most probable soil class predicted by Random Forests models in forest areas in the upper Choptank River Watershed, Maryland and Delaware. Values closer to one indicate greater uncertainty in assigning soil class.
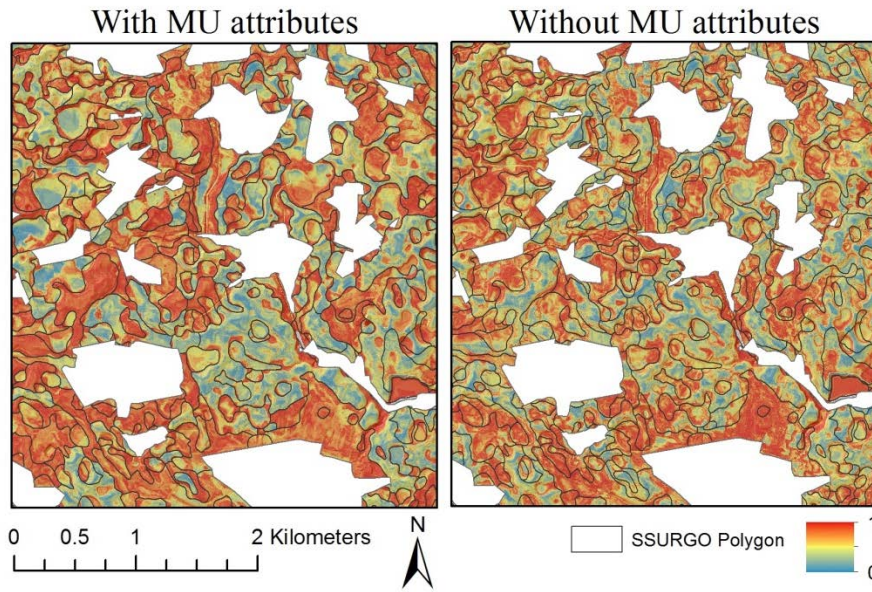
Figure 3.13 Confusion between the most probable and second most probable soil drainage group predicted by Random Forests models in cropland areas in the upper Choptank River Watershed, Maryland and Delaware. Values closer to one indicate greater uncertainty in assigning soil class.

3.3.5 Model validation

Overall accuracy was high in both forest models, with 77.1% of validation pedons correctly predicted by the drainage group model ($\kappa = 0.54$) and 70.6% of validation pedons correctly predicted by the texture group model ($\kappa = 0.45$) Examination of user's accuracies (number correctly predicted class y/total predicted class y) and producer's accuracies (number correctly predicted class y/total actual class y), however, shows that class error was imbalanced (Tables 3.6 & 3.7). In cropland areas, overall accuracy was 50% for both drainage group models ($\kappa = 0.31$ with SSURGO, $\kappa = 0.30$ without SSURGO). SSURGO drainage class (mapped as dominant condition) was a slightly better predictor than both models, predicting 56% of validation pedons correctly ($\kappa = 0.39$) (Table 3.8).

Table 3.6 Validation point accuracy of drainage group predictions by Random Forests models in forested areas in the upper Choptank River Watershed, Maryland and Delaware; overall accuracy 77.1%, κ = 0.54.

	Reference			
Predicted	VPD/PD	SWPD/MWD	WD	User's Accuracy
VPD/PD	41	8	1	82.0%
SWPD/MWD	3	8	4	53.3%
WD	0	0	5	100.0%
Producer's Accuracy	93.2%	50.0%	50.0%	

Table 3.7 Validation point accuracy of texture group predictions by Random Forests models in forested areas in the upper Choptank River Watershed, Maryland and Delaware; overall accuracy 70.6%, κ = 0.45.

	Reference		
Predicted	Coarse	Fine	User's Accuracy
Coarse	24	6	80.0%
Fine	17	21	55.2%
Producer's Accuracy	58.5%	77.8%	

Table 3.8 Validation point accuracy of drainage group predictions by Random Forests models in cropland areas in Upper Choptank River Watershed, Maryland and Delaware: (a) with mapunit covariates, (overall accuracy 50.0%, κ = 0.31); and (b) without map unit covariates, (overall accuracy 50.0%, κ = 0.30). (c) Validation of Soil Survey Geographic Database (SSURGO) drainage class (dominant condition) in cropland areas (overall accuracy, 55.6%, κ = 0.39).

(a)

	Reference				
Predicted	VPD	PD	SWPD/MWD	WD	User's Accuracy
VPD	7	4	0	0	63.6%
PD	7	13	6	7	39.4%
SWPD/MWD	0	0	1	0	100.0%
WD	1	3	8	15	55.6%
Producer's Accuracy	46.7%	65.0%	6.7%	68.2%	

(b)

	Reference				
Predicted	VPD	PD	SWPD/MWD	WD	User's Accuracy
VPD	4	0	1	1	66.7%
PD	10	17	6	6	43.6%
SWPD/MWD	0	0	0	0	NA
WD	1	3	8	15	55.6%
Producer's Accuracy	26.7%	85.0%	0.0%	68.2%	

(c)

	Reference				
Predicted	VPD	PD	SWPD/MWD	WD	User's Accuracy
VPD	8	1	0	0	88.9%
PD	4	10	3	1	55.6%
SWPD/MWD	3	2	4	3	33.3%
WD	0	7	8	18	54.5%
Producer's Accuracy	53.3%	50.0%	26.7%	81.8%	

3.4 General discussion

Overall, our model predictions fit our understanding of variability in natural soil drainage class and texture class on depressional wetland landforms in forested areas. Resulting soils maps provide a higher level of spatial detail for natural soil drainage and texture class than current SSURGO maps as well as a measure of uncertainty that is linked to terrain. The relative success of the forest model compared to the crop model illustrates both the advantages provided by lidar-derived elevation data and the challenges of capturing the soil surveyor's mental model in a highly engineered, low-relief landscape.

Several factors could contribute to higher accuracy in forest areas: less human modification of the landscape in forest areas; differences in the natural variation in soil properties in forest vs. cropland; and the nature of the training data used in forest vs. cropland. Most of the Choptank River basin was forested when Europeans first arrived in the mid-seventeenth century. By 1800, virtually all arable land had been deforested, with remaining forest limited primarily to poorly drained stream corridors that were too wet to farm (Fisher et al., 2006). Ditches are common in currently forested areas, indicating that attempts were made in the past to drain them but were unsuccessful (Denver et al., 2014).

The topographic metrics we derived may be better able to capture natural soil variation in forest vs. cropland in our study area. The majority of training data used in forested areas were compiled from previous field studies in which transects were run from the center of depressions outward using a random, stratified design with GPS locations. By contrast, training data used in the cropland model were compiled by local soil survey staff, which did not include GPS locations and were collected in an effort to map the entire landscape,

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not just the Delmarva Bay landforms. Most machine learning classifiers are trained with

the assumption that the classifier is run using data that is drawn from the same

distribution as the training data (Provost, 2000). Imbalanced training data (when the

number of observations belonging to one class is much lower than those belonging to

other classes) can result in poor classification accuracy for the minority classes in

Random Forests (Chen et al., 2004) Both the forest and cropland models were trained on

imbalanced data, but the actual class distribution on Delmarva bay landforms may have

been better represented by the training data in forest than on cropland.

Because much of the forested area in the region was mapped as complexes, the use of

pedon data was critical in training our Random Forests model on forest land. Approaches

to training by sampling legacy soil maps include: 1) using the full extent of map unit

delineations for training single component map units and rule matching to create training

areas for components in soil associations (Nauman and Thompson, 2014); 2) sampling

map unit delineations based on the percentage of series components using normalized

possibility distributions (Subburayalu et al., 2014); 3) using weighted random choice

assignments to points sampled from map unit delineations (Odgers et al., 2014b); and 4)

using fuzzy membership functions to relate combinations of environmental factors to

mapped soil classes (Yang et al., 2011). Training by sampling legacy soil maps would

have been very difficult to employ in our study area since the topography is so subtle, the

landforms of interest were often mapped as complexes in forest areas, and there were so

many soil series mapped in the cropland areas. There was also little information in

SSURGO tables that could be used to differentiate soil classes through rule matching. By

using field data collected from previous research and local soil surveyors to train our

models, we developed a DSM approach that makes use of existing field data that were not in an existing pedon database and demonstrates that Random Forests can produce accurate predictions using a limited number of training observations in a low relief landscape.

There are challenges to using field data when there are a limited number of training points and large number of soil components, often resulting in class imbalance. In our study area, both drainage and texture groups were highly imbalanced, resulting in considerable variability in training and validation accuracies across classes. Brungard et al. (2015) also found that classification accuracy in DSM models was highly dependent on the frequency distribution of pedon observations, with fewer pedon observations resulting in lower classification accuracy for that class. Potential ways to deal with a large number of classes and class imbalance include increasing the number of observations for classes with few observations or decreasing the number of classes (Brungard et al., 2015). For example, Kempen et al. (2009) aggregated 96 map units into ten map units when using DSM to update the national soil survey map of the Netherlands. Häring et al. (2012) enforced a proportion of 2:1when randomly sampling training pedons in cases where there was more than twice as much of one soil class compared to the other soil class in map unit complexes.

Soil classes were aggregated to the extent that the resulting maps would still be useful for updating legacy soils maps and informing wetland conservation and restoration decisions. We also experimented with class weighting schemes but this did not improve prediction of the less well represented classes based on training accuracy and visual examination of map output.

Although aggregating soil classes did help us construct models that provide greater spatial detail than traditional soil maps, it is important to note that we lose a considerable amount of information that is present in the polygon structure of the original maps. SSURGO polygons relate to a rich database of information on soil properties and interpretations. The simplified soil classes we created relate only to drainage class or texture. Operationally, models such as these are not a replacement for traditional soil survey methods, but could be very useful for updating existing soil maps by providing accurate soils information that cannot be mapped using traditional methods.

One of the objectives of this research was to identify which topographic attributes can best predict variability in soil hydrologic and depositional processes in low-relief landscapes. We chose a limited number of topographic metrics based on previous research in the region and project goals, and overall results aligned with our understanding of hydrologic and depositional processes controlling soil drainage and texture class. We found that one of the challenges in developing DSM methods in highly modified low-relief landscapes is deciding which filtering algorithms and neighborhood sizes to use when preparing lidar-derived elevation metrics. In order for these methods to be repeated in other low-relief landscapes, careful consideration of filtering algorithms and neighborhood sizes in preparing terrain covariates will be necessary.

The models developed in this study were not able to distinguish VPD and PD drainage classes in forested areas, illustrating the limitations of relying on topographic variables to disaggregate natural soil drainage class. VPD soils have the highest carbon accumulation, so identification of these areas is important for improving our understanding of carbon sequestration and denitrification functions of these wetlands. Where adequate nitrate is

available, it is likely that VPD soils would have higher denitrification rates than PD soils because of higher carbon, shallower depth and greater frequency/duration of anaerobic conditions. Previous studies on the Delmarva Peninsula have attributed lower nitrate concentrations in the poorly drained uplands region (compared to the well-drained uplands) to denitrification in anoxic groundwaters and dilution of high nitrate oxic groundwater by wetlands (Denver et al., 2014; Phillips et al., 1993). It is difficult to evaluate ground water influence on wetland hydroperiod based solely on topography. For example, water table mounding is common beneath depressional wetlands in the upper Choptank, indicating that water table gradients do not always follow topographic gradients (Denver et al., 2014).

SSURGO soil maps are representations of the soil surveyor's knowledge of the distribution of soils in the landscape (Bui, 2004). The SSURGO-derived ADJ MU attribute was developed in an effort to include information on soil relationships beyond what is encompassed in individual map units. This attribute incorporated SSURGO information from a 200 m neighborhood surrounding each 3 m grid cell. DSM techniques offer the opportunity to combine knowledge of soil geography with a vast array of digital environmental data using advanced statistical methods, with soil systems representing the bridge between existing knowledge and digital data (De Gloria et al., 2014). Incorporating high cardinality categorical variables such as SSURGO soil classes in predictive models is challenging, however. In forested areas, SSURGO attributes were not important predictors, likely due in part to the lack of variability in attribute values. On cropland, our model was extremely sensitive to the inclusion of the categorical SSURGO attributes, with output maps following SSURGO delineations and ADJ MU transitions

closely. Validation results were the same though whether or not SSURGO attributes were included. A better approach to represent soil systems in developing attributes may be to derive terrain (and other) metrics at multiple scales. Since soil forming processes operate at varying scales, patterns observed at one scale may not be observed at other scales (Miller and Schaetzl, 2016). Behrens et al. (2010) and Lindsay et al. (2015) offer frameworks for investigating scale effects in deriving terrain metrics which could be useful for incorporating soil systems knowledge in DSM.

3.5 Conclusions

Our study indicates that DSM techniques can be used with legacy profile data to create maps that depict natural soil drainage class and texture class on Delmarva Bay landforms in forested areas better than conventional soil maps. Model predictions have the potential to improve watershed models in depressional wetland landscapes by contributing higher spatial detail as well as a quantitative measure of uncertainty. The attribute importance measures can also inform our understanding of wetland hydrology and elucidate future research needs for advancing our understanding of hydrologic and depositional processes in these landscapes. Depressional wetlands (e.g., Carolina bays) occur along the Atlantic Coastal Plain from Florida to New Jersey; thus the methods developed here could be applied to other forested depressional wetland landscapes where lidar data are available.

Future research should examine methods for incorporating information on dynamic controls on wetland hydrology in modeling natural soil drainage class, and creating new metrics that account for multiple controls.

Chapter 4 – Natural Soil Drainage Class and Inundation Dynamics in Forested

Depressional Wetlands in the Choptank Watershed, Maryland

4.1 Introduction

The establishment of effective wetland conservation and restoration practices depends on accurate information on wetland location and extent. Field mapping of wetlands is time and cost-prohibitive at the landscape scale, so wetland mapping methods often rely on remote observations and expert knowledge (Lang et al., 2013). On the Mid-Atlantic Coastal Plain, wetlands are frequently forested, and the extent and degree of saturation and inundation can be highly variable, both spatially and temporally (Huang et al., 2014; McCarty et al., 2008). Depressional wetlands, which are numerous across the Coastal Plain, exhibit a range of hydroperiods – from rarely inundated to semipermanently inundated (De Steven and Lowrance 2011). On the Delmarva Peninsula, depressional wetlands (commonly Delmarva bays) are typically small (~2 ha) with low relief (~1 m) (Fenstermacher et al., 2014). The combination of forest cover, variable hydroperiod, small size, and low relief make these wetlands some of the most challenging to map and monitor (Lang et al., 2013; Tiner, 1990). Depressional wetlands provide a range of ecosystem services, including water purification, groundwater recharge, provision of critical habitat, and carbon storage; therefore the ability to monitor these wetlands is not only important for determining their location and extent but also for understanding their functions and establishing effective conservation and restoration practices (Fenstermacher et al., 2016; Sharitz and Gibbons, 1982; Tiner, 2003).

Traditionally, wetland mapping primarily relied on a combination of aerial photography, photointerpretation techniques, and field verification (Lang and McCarty, 2008). Recently, advances in remote sensing technology have led to the development of new approaches using a variety of remotely sensed data types, including lidar and multi-temporal Landsat imagery, to map wetlands in low-relief landscapes. On the Delmarva Peninsula, topographic metrics including local relief and a multiple-flow direction based topographic wetness index have been shown to be good predictors of wetland location (Lang et al., 2013). Lidar intensity data collected during peak hydrologic expression has been used to accurately map inundation below the forest canopy (Lang and McCarty, 2009). A novel approach combining lidar intensity and Landsat time-series imagery has been developed in this region to map wetland inundation change over time (Huang et al., 2014), resulting in a long-term wetland inundation monitoring product. The inundation product consists of maps of subpixel water fraction (SWF) indicating the percent of surface water in each 30 m pixel for the years 1985 – 2011 (Jin et al., 2017). Accuracy assessments of the SWF maps indicate that they can be used to extract long-term information on inundation dynamics with relatively low degrees of uncertainty (Jin et al., 2017).

While inundation time series maps provide valuable insights into wetland extent and hydroperiod, some wetlands rarely exhibit surface inundation and instead contain soils that are saturated within the root zone. For this reason, surface water extent maps may not detect these wetland areas and could thus omit areas with hydric soils. Hydric soils are soils that are "formed under conditions of saturation, flooding or ponding long enough during the growing season to develop anaerobic conditions in the upper part" (Federal

Register July 13, 1994). Wetlands, as defined by the U.S. Army Corps of Engineers and

the U.S. Environmental Protection Agency for Section 404 of the Clean Water Act (U.S.

Army Corps of Engineers, 1987), are:

> "Areas that are inundated or saturated by surface or ground water at a frequency
>
> and duration sufficient to support, and that under normal circumstances do
>
> support, a prevalence of vegetation typically adapted for life in saturated soil
>
> conditions . . ."

Hydric soils, along with wetland hydrology and hydrophytic vegetation, are a

fundamental component of wetlands. By excluding areas that are saturated but not

ponded, inundation maps likely underestimate wetland extent, omitting areas with unique

physicochemical properties and biota.

Digital soil mapping techniques (DSM) show promise for improved mapping of wetland

soil properties. DSM involves using qualitative "knowledge-based" and/or quantitative

predictive models to map soil properties and classes (Bui, 2004; McBratney et al., 2003).

One approach is to spatially disaggregate soil information within areas where multiple

soil classes have been grouped together (Bui and Moran, 2001; Häring et al., 2012;

Nauman et al., 2014; Nauman and Thompson, 2014; Odgers et al., 2014b; Subburayalu

and Slater, 2013). Chapter 3 describes disaggregation methods in which topographic

metrics were used to accurately map natural soil drainage class – an indicator of the

frequency and duration of soil saturation/inundation – in forested depressional wetlands.

Natural soil drainage class is defined by the conditions under which the soil was formed;

it includes seven classes ranging from excessively drained to very poorly drained.

Wetland soils generally fall in the very poorly or poorly drained classes, and sometimes in the somewhat poorly drained class. A limitation of the disaggregation methodology described in Chapter 3 was that it was not able to distinguish very poorly drained from poorly drained soils. Very poorly drained soils are wet for most of the growing season and frequently ponded, whereas poorly drained soils are typically wet at or near the surface for part of the growing season. In the field, the thickness and darkness of the A horizon – indicators of the amount of organic matter in the soil – are used to distinguish the two classes. Differences in frequency and duration of wet periods affect organic accumulation, decomposition, soil and water chemistry, nutrient cycling, species composition, and primary productivity in wetlands (Mitsch and Gosselink, 2007). Hence the distinction between very poorly and poorly drained soils is important for understanding wetland function and thus supporting natural resources decision-making.

Together, the disaggregated soils map and inundation maps can potentially provide a comprehensive picture of the extent of saturated soils and inundation dynamics in forested depressional wetlands on the Delmarva Peninsula. The inundation maps were not originally included in the disaggregation study because the final products were not complete at the time the disaggregation model was built. The disaggregation methods were also intended to be repeatable in similar landscapes, so only data that were broadly available were used as predictors. The omission of information on soil saturation and inundation derived from optical imagery was recognized as a limitation of the study in Chapter 3. Leaving the inundation maps out of the model, however, allowed for an additional independent validation of the disaggregation results and evaluation of the advantages and limitations of each product. The disaggregated soils map can potentially

help identify wetland areas not captured by the inundation maps, and the inundation maps can potentially help distinguish soils that are likely very poorly vs poorly drained in the disaggregated soils map. For example, in areas mapped as poorly or very poorly drained, zones that are semipermanently inundated are likely very poorly drained, whereas zones that are rarely inundated are likely poorly drained. Furthermore, a comparison of the topographic metrics (a measure of potential wetness), with the inundation data (a measure of actual wetness), may elucidate why the disaggregation model was unable to distinguish very poorly drained from poorly drained soils.

I conducted an exploratory data analysis of the inundation dataset in forested depressional wetlands on the Mid-Atlantic Coastal Plain for the purpose of examining how these products complement each other and how they can best be leveraged to map wetland soils and inform predictions of wetland function. My objectives were to:

1. Compare the disaggregated soil drainage class map with the inundation maps;
2. Identify zones within areas mapped as very poorly drained/poorly drained that show stable, variable, or consistently low inundation patterns;
3. Compare the topographic metrics with the inundation data; and
4. Suggest potential avenues of research for investigating uses of the inundation data in wetland soils mapping.

Stable and variable inundation patterns are defined here based on the constancy of surface water presence during the season of peak inundation over time. This distinction can have important implications for soil characteristics and wetland function. The frequency at which wetland depressions are seasonally inundated influence wetland

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hydrology and surface water connections which can affect soil development, organic matter accumulation, cation exchange capacity, water chemistry, vegetation communities, fish assemblages, amphibians and other fauna (Cook and Hauer, 2007; Sharitz, 2003; Sharitz and Gibbons, 1982; Snodgrass et al., 2000, 1996). For example, areas that are regularly inundated (stable) create an anaerobic environment that allows accumulation of soil carbon (Fenstermacher et al., 2016) and conversion of nitrate to gaseous nitrogen through denitrification (Goldman and Needelman, 2015); areas that are occasionally inundated from year to year (variable) may provide critical habitat for certain species of amphibians that are characteristic of areas with shorter hydroperiods (Snodgrass et al., 2000). Within very poorly/poorly drained areas in the disaggregated soils map, it is predicted that very poorly drained soils occur primarily in stable inundation zones, poorly drained soils occur in zones with consistently low to no inundation, and there is greater uncertainty in drainage class in variable inundation zones.

4.2 Methods

4.2.1 Study area

The study area was located in the upper Choptank River watershed on the Delmarva Peninsula (Fig. 4.1). The Choptank River drains the central Delmarva Peninsula in Maryland and Delaware. The 1756 km^2 watershed is relatively flat, with a maximum elevation of less than 30 m above sea level (Lee et al., 2000). Land cover in the Choptank Watershed is dominated by agriculture (65%), with smaller amounts of forest (26%) and urban areas (6%) (Fisher et al., 2006). The study was conducted in the "poorly drained

uplands" hydrogeomorphic subregion of the Choptank watershed. This subregion is characterized by relatively slow streams running across a low topographic gradient, poorly incised valleys, and shallow water tables (within 3 m of land surface) (Hamilton et al., 1993). The study area was selected based on the high density of forested, seasonally inundated depressions (Fig. 4.2a). To focus the study on depressional wetlands, floodplain soils in the U.S. Soil Survey Geographic Database (SSURGO) were identified and excluded from analysis, thereby avoiding most riparian wetlands (Fig. 4.2b). Wetland flats also occur in the study area but are more difficult to discern from depressional wetlands and were not distinguished from depressional wetlands. Forested areas were identified using the National Landcover Dataset (NLCD forest and woody wetland classes) (Homer et al., 2015).

Figure 4.1 Location of study area in the upper Choptank River Watershed (outlined in black) on the Delmarva Peninsula (Basemap source: Esri (2013)).

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(a)   (b)
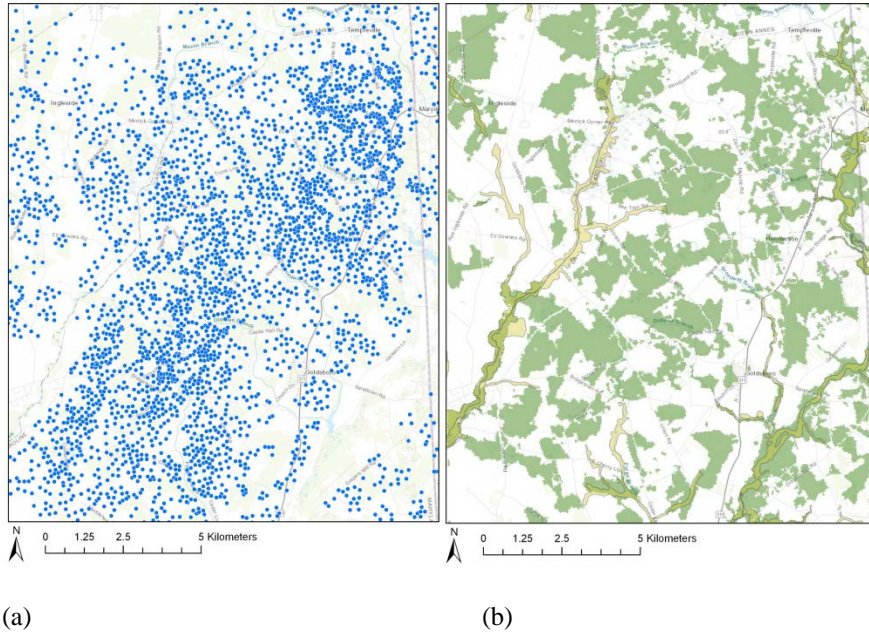
Figure 4.2 Maps of the study area in the upper Choptank River Watershed showing: (a) locations of depressional wetlands identified in lidar digital elevation models (Fenstermacher, 2012); and (b) National Landcover Database (NLCD) forest (green) and Soil Survey Geographic Database (SSURGO) floodplain soils (yellow) (Basemap Source: Esri (2013)).

4.2.2 Soil drainage class maps

Three meter resolution natural soil drainage class maps were created using the methods described in Chapter 3. Drainage classes were grouped into three categories: very poorly to poorly drained (VPD/PD), somewhat poorly to moderately well drained (SWPD/MWD) and well drained (WD).

4.2.3 Inundation maps

The inundation maps were obtained from the Agricultural Research Service, United

States Department of Agriculture (ARS-USDA) in Beltsville, MD. The data were derived

from lidar intensity data (Lang et al., 2013; Lang and McCarty, 2009) and Landsat time-

series imagery collected from 21 years during the period 1985 - 2011, covering the entire

Delmarva Peninsula (Huang et al., 2014; Jin et al., 2017). All Landsat images were spring

images (March-April) collected during the peak inundation period (end of leaf-off). To

create the maps, field-validated lidar intensity data were used to derive reference

inundation data at 1 m resolution (Lang et al., 2012), which were then aggregated to

calculate subpixel water fraction (SWF) at 30-m resolution. Regression trees were used to

model relationships between SWF and Landsat surface reflectance (6 spectral bands) and

a suite of spectral indices. The derived model was then used to predict SWF in different

years and over areas where reference data were not available (Huang et al. 2014). The

data include 30 m resolution (SWF) maps and Principal Components Analysis (PCA)

maps derived from the SWF time-series. Methods for developing the SWF maps are

described in detail in Huang et al. (2014) and Jin et al. (2017). SWF maps of the study

area are displayed in Figure 4.3.

PCA is a mathematical technique for reducing dimensionality of datasets with a large

number of variables. The first principal component (PCA 1) is the linear combination of

variables that has maximum variance. PCA 1 accounts for as much of the variability in

the inundation time-series as possible. Each succeeding component accounts for as much

of the remaining variability as possible. PCA is one of the simplest and most robust ways

to reduce data dimensionality without losing too much information. For time series data,

PCA is often preferable to taking the mean across years, which does not reflect inter-annual variability.
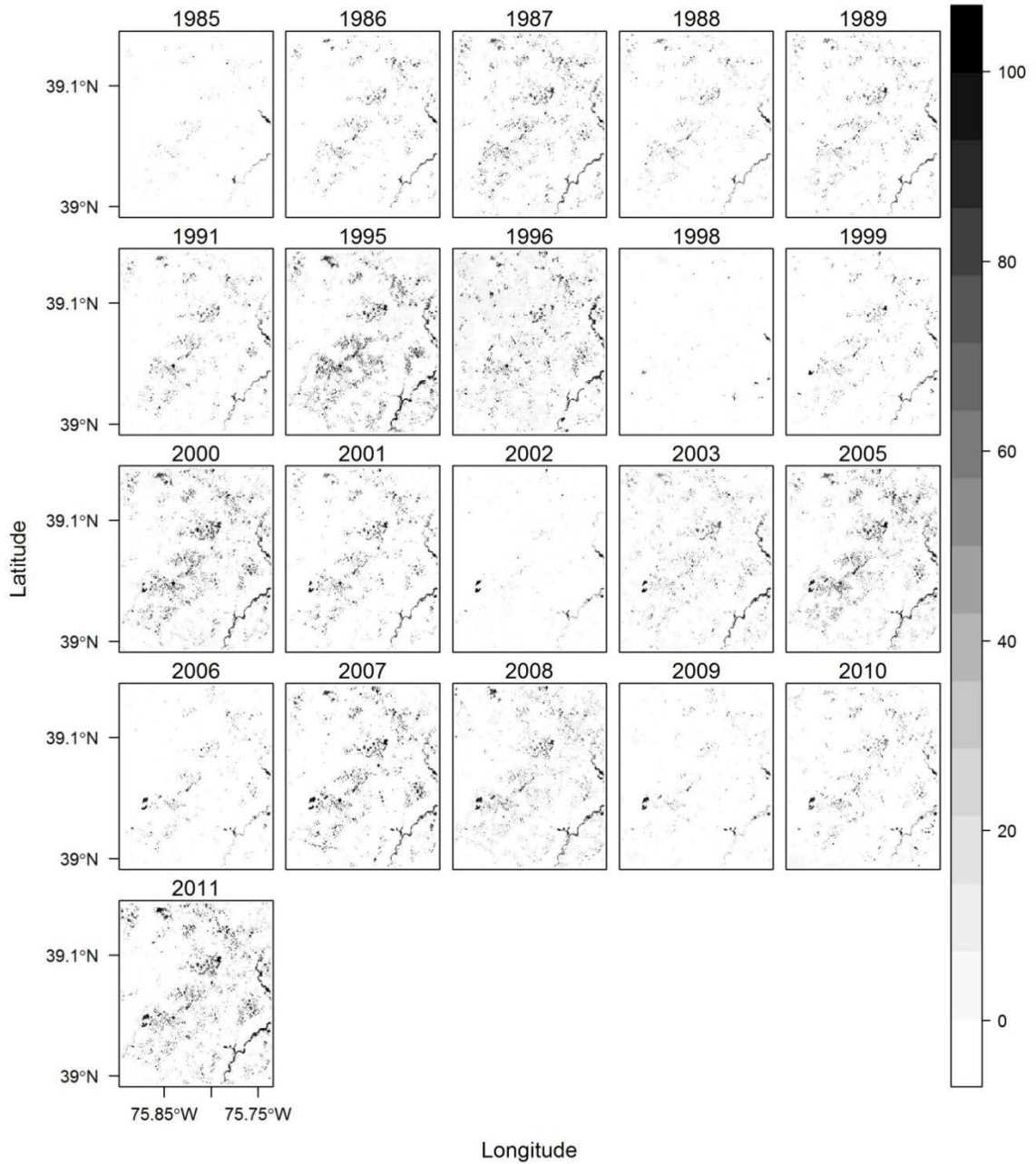
Figure 4.3 Sub-pixel water fraction (SWF) maps of the study area in the upper Choptank River Watershed, 1985 - 2011. SWF values represent the percent of surface water in each 30 m pixel; values were derived from lidar intensity data (Lang et al., 2013; Lang and McCarty, 2009) and Landsat time-series imagery (Huang et al., 2014; Jin et al., 2017).

R statistical software (v. 3.4.2) was used to calculate total inundated area (weighted by percent) in the study area over time (Figure 4.4). Inundation was highly variable across years, with nearly no inundated area in 1985, 1998, and 2002 and highest inundation in 1995, 2000, and 2011. Of the 76 km^2 of non-floodplain forest in the study area, approximately 16% was inundated in the wettest year, 1995.
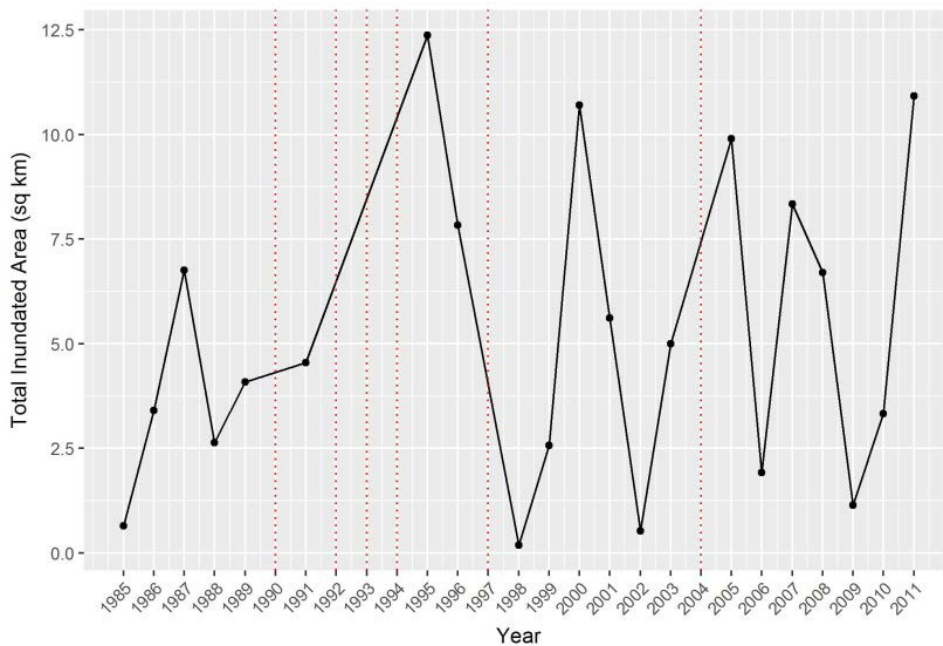
Figure 4.4 Total inundated area derived from subpixel-water fraction maps (excluding floodplains) in study area in upper Choptank River Watershed over time. Red dotted lines indicate years for which there were no inundation data.

4.2.4 Comparison of inundation and disaggregated soils maps

First, the disaggregated soils map was visually compared with the first band of the PCA in ArcGIS Pro 2.1 software (Esri, 2011). Only PCA 1 was used because it captures 97% of the variation in the inundation data. Next, the SWF raster layers were converted to

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points to create a point shapefile with SWF values for all 21 years using the Raster to Point tool in ArcGIS. Points were defined at the centers of raster cells. Points on floodplains or non-forest were removed. Since the disaggregated soils map is 3 m resolution and the inundation data are 30 m resolution, the focal statistics tool in ArcGIS was used to determine the majority drainage group value within a 30 x 30 m neighborhood in order to compare with the 30 m SWF maps. The majority drainage group values were then extracted to the point shapefile. This resulted in some NA values in areas where there was no majority drainage group. Points were then exported to R for analysis. Average SWF and total inundated area were calculated for each drainage group by year and the Kruskal-Wallis test was used to test for differences in average SWF across drainage groups.

4.2.5 Identification of inundation zones

To identify stable vs variable inundation zones in forested depressional wetlands, wetland extent was first defined as those areas mapped as VPD/PD in the disaggregated soils map. This may exclude a small fraction of wetland soils that fall in the SWPD natural soil drainage class (SWPD/MWD group). The VPD/PD regions cover a greater extent than what is indicated as periodically inundated by the SWF maps. This may be because the SWF maps represent current hydrologic conditions, whereas the soils maps represent historical hydrologic conditions, and SWF maps do not capture areas that may be saturated near the surface but not periodicall inundated. To prepare the maps for analysis, ArcScan tools were used to smooth the maps by cleaning up isolated pixels (Esri, 2011).

The classified drainage group raster was then converted to polygon, and non-forest areas and floodplain soils were clipped out. Small polygons (< 0.001 km^2) were removed (Fig. 4.5). SWF points falling within VPD/PD polygons were exported to R to determine mean and variance in SWF values at each point across the entire time series.
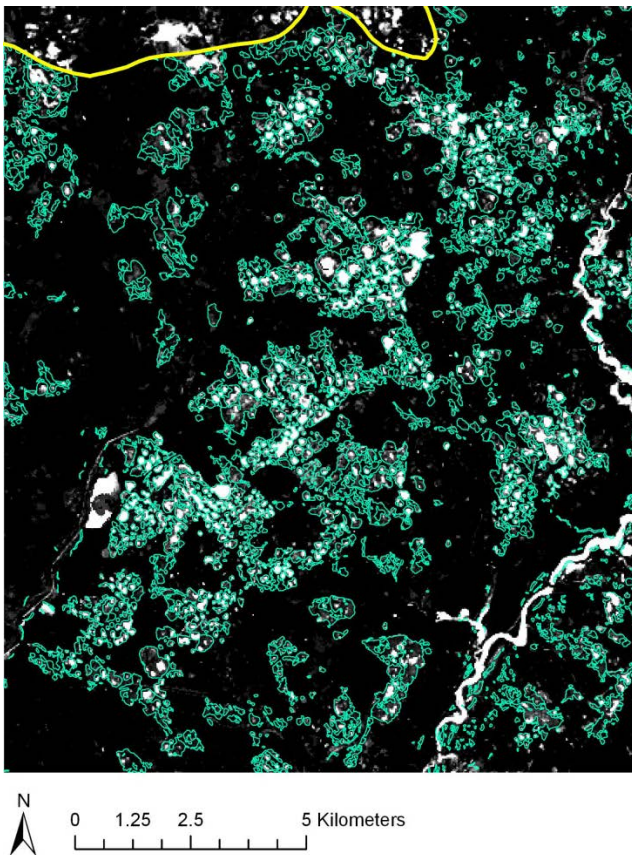
Figure 4.5 Polygons of very poorly and poorly drained soils from the disaggregated soils map in the upper Choptank River Watershed overlaid on the first band of the Principal Components Analysis (PCA) of the inundation time-series. White areas represent areas with higher inundation. Yellow boundary marks the northern extent of the disaggregated soils map.

The ArcGIS Grouping Analysis tool was used to identify areas with more stable vs variable inundation patterns. The Grouping Analysis tool uses a K Means clustering

algorithm to group features so that features within groups are as similar as possible and groups themselves are as different as possible. Feature similarity is based on a set of attributes specified by the user (Esri, 2011). To identify areas that have more stable vs variable inundation patterns, mean and variance in SWF values across all 21 years of data were used to define groups. The user chooses the number of groups to create. Based on visual examination of the inundation time-series, three groups were selected with the expectation that the algorithm would be able to distinguish areas with consistently high SWF values (stable), highly variable SWF values (variable), and consistently low SWF values. Only a small fraction of forest in the study area was expected to fall in the stable category since in some years the entire study area appears to have very little inundation (Fig. 4.3).

4.2.6 Topographic metrics and inundation data

Topographic metrics were developed using a DEM derived from lidar data collected in 2013 - 2014 as part of the post-Hurricane Sandy lidar collection in DE and MD. The topographic metric analysis was limited to the Caroline County, MD portion of the study area, where lidar data were collected in December, when seasonal inundation was low, allowing for development of a more accurate bare-earth DEM. One meter DEM tiles were downloaded from the USGS National Map (U.S. Geological Survey, 2017), mosaicked, resampled to 3 m using cubic convolution and projected to UTM (12N WGS 84).

A sink index (SINK), a topographic wetness index (TWI) and a local elevation index (LELEV) were generated using the same methods described in Chapter 3. SINK is a measure of the likelihood a raster cell is a sink – a location with no surface water outlet. TWI is a measure of potential surface saturation based on catchment area and slope. LELEV is a measure of relative topographic position within a 200 m radius. For comparison with the 30 m SWF data, the 3 m topographic metric surfaces were smoothed by calculating the average value in a 30 m neighborhood using the focal statistics tool in ArcGIS. Values were then extracted to the points in forested areas. Points within 60 m of floodplain soil polygons or 30 m of ditches or forest edges were removed. A 30 m buffer was chosen for ditches in order to remove points within ditches and on berms alongside ditches. It is possible that ditches may affect surface inundation beyond this 30 m buffer, which is recognized as a source of uncertainty in this analysis. Remaining points were checked against imagery of the study area and those falling on infrastructure, patches of cleared land, and ponds/reservoirs were removed. Points were exported to R and distributions of each metric were examined and compared with the inundation PCA to explore their potential usefulness in predicting inundation within forested areas.

4.3 Results and Discussion

4.3.1 Comparison of SWF and disaggregated soils maps

The first band of the PCA was compared with the drainage groups in the disaggregated soils map (Fig. 4.6). Within forested areas, the majority of the soils were mapped as VPD/PD, indicating much of the area is periodically saturated or inundated (Table 4.1).

The brightest areas in the PCA correspond well with the VPD/PD drainage group, but do

not cover as great an extent. The brightest areas are frequently in the centers of

depressions.
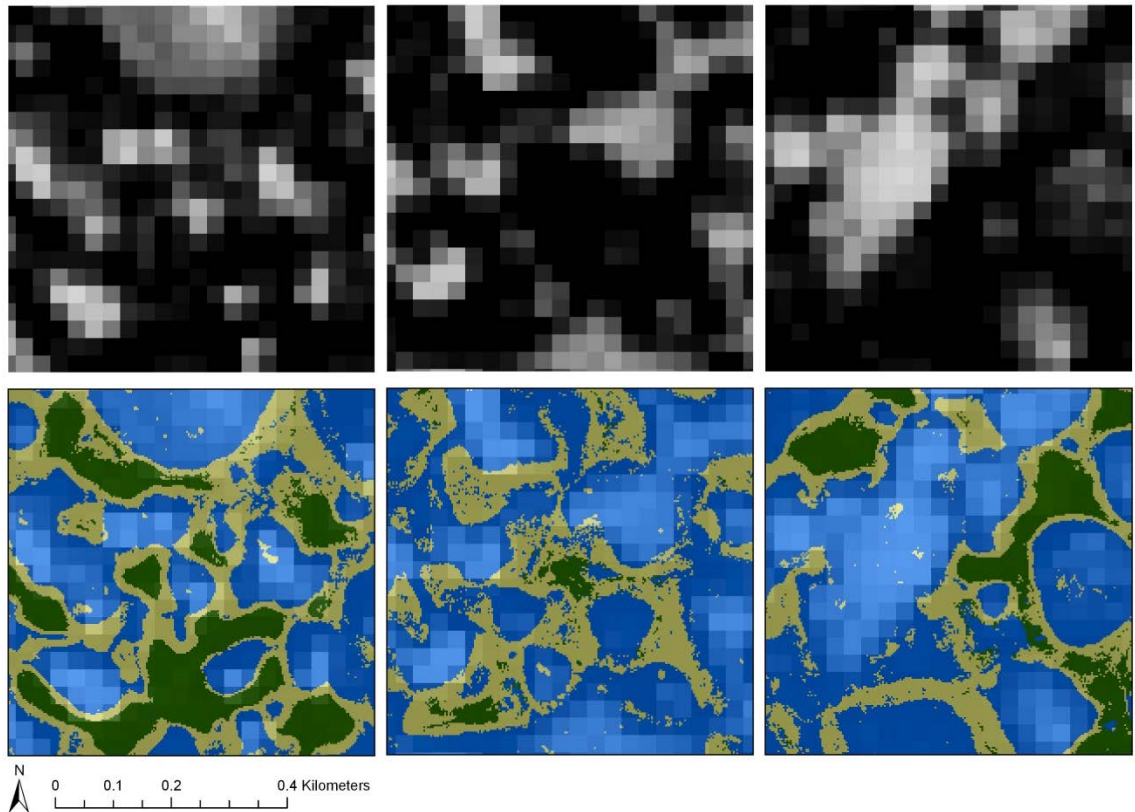
Figure 4.6 Zoomed-in maps of the study area showing: *Top*: band 1 of the Principal
Components Analysis (PCA) of the inundation time-series; and *Bottom*: Drainage groups
classified by the disaggregation model with the semi-transparent PCA overlaid on top.
Blue shades are classified as very poorly drained/poorly drained; yellow shades are
classified as somewhat poorly drained/moderately well drained; green shades are
classified as well drained. Lighter shades have higher PCA values. Highest PCA values
tend to occur in the centers of depressions (light blue).

Table 4.1 Total area in each drainage group (majority group in 30 m neighborhood) in forested areas (excluding floodplains) in the upper Choptank River Watershed. VPD/PD = very poorly drained/poorly drained; SWPD/MWD = somewhat poorly drained/moderately well drained; WD = well drained; NA = not classified.

Drainage Group	VPD/PD	SWPD/MWD	WD	NA
Area (km^2)	45.6	19.9	5.4	0.39
% Total Area	63.9	28.0	7.6	0.55

Average SWF and total inundated area by drainage group over time are displayed in Figure 4.7. SWF values were consistently highest in the VPD/PD areas. Boxplots of average SWF are shown in Figure 4.8. The Kruskal-Wallis rank sum test was used to test for differences in average SWF between drainage groups. The results of the Kruskal-Wallis test were significant (H = 22.6, df = 3, p = 0.000048).

(a)

(b)
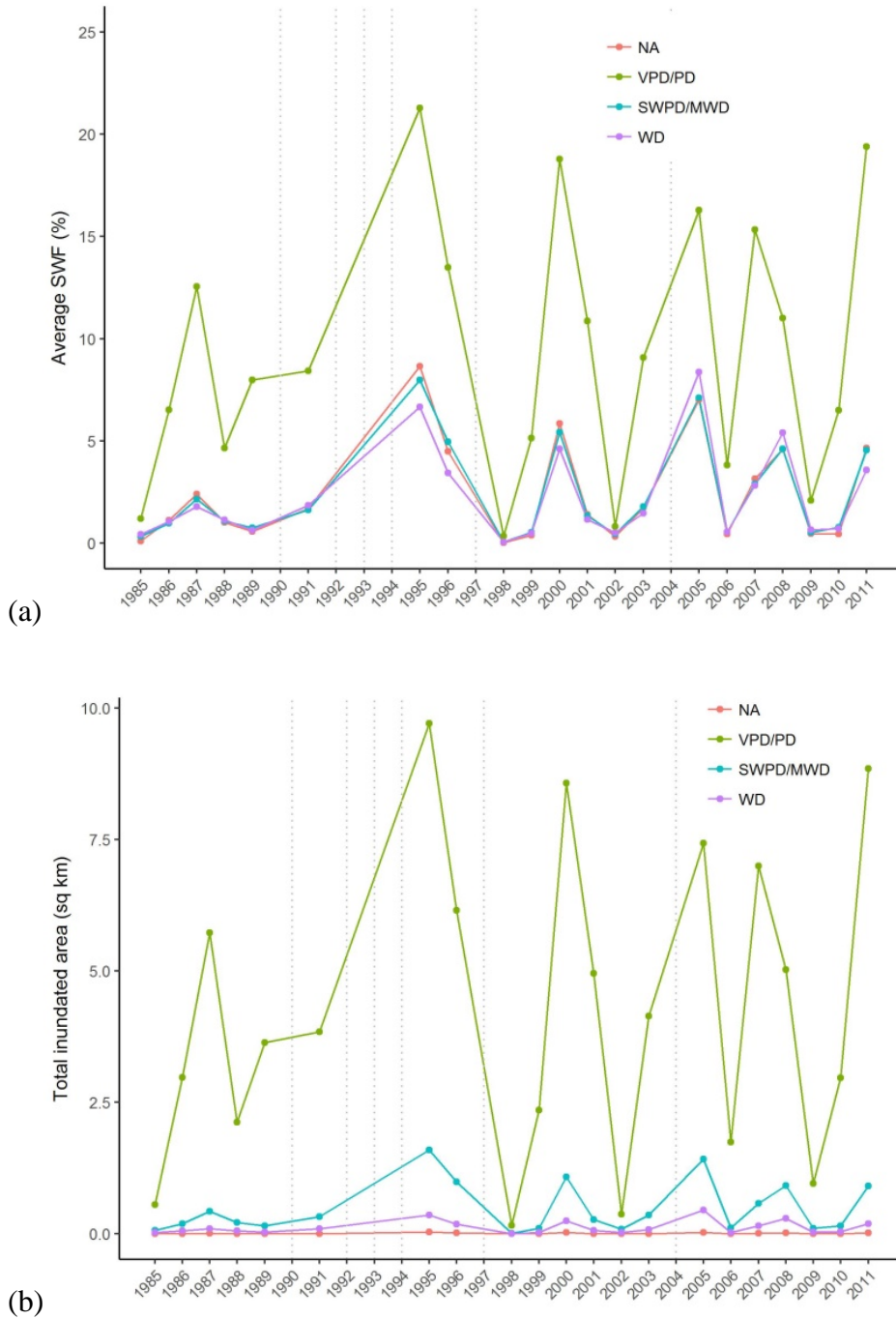
Figure 4.7 (a) Average sub-pixel water fraction (SWF) by soil drainage group over time. (b) Total inundated area (weighted by percent) by drainage group over time. Dotted grey lines indicate years with no data. VPD/PD = very poorly drained/poorly drained; SWPD/MWD = somewhat poorly drained/moderately well drained; and WD = well drained.
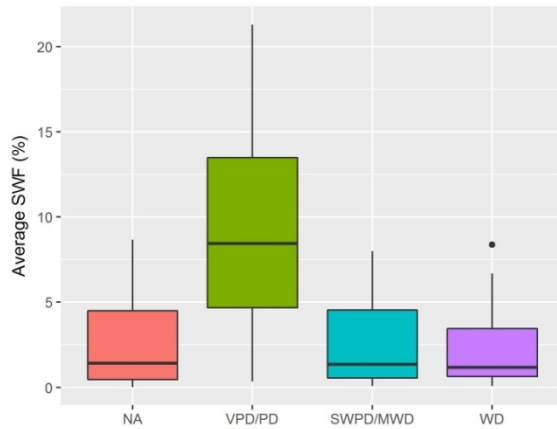
Figure 4.8 Boxplots of average sub-pixel water fraction (SWF) values by soil drainage group. VPD/PD = very poorly drained/poorly drained; SWPD/MWD = somewhat poorly drained/moderately well drained; and WD = well drained.

4.3.2 Identification of inundation zones

The grouping analysis was able to distinguish three groups based on average SWF and variance in SWF over time, but was not able to differentiate areas with stable inundation. SWF average and variance values are summarized by group in boxplots and density plots in Figure 4.9. One group shows consistently low inundation (L). The other two groups show variable inundation; these groups are distinguished as variable low (VL) and variable high (VH). The majority of points (74%) fall in group L (Table 4.2). The results are displayed in a map in Figure 4.10. VH points appear to correspond frequently with the centers of depressions, bordered by VL points. L points tend to occur more toward the edges of depressions, but in some areas nearly entire depressions fall in group L. Zooming into these areas, however, shows that drainage ditches often occur within or near these depressions (Figure 4.11).

Time series of distributions of SWF values are displayed in Figure 4.12a and average

SWF values by year are displayed in Figure 4.12b. From the time series, it is evident how

variable inundation is from year to year within forested depressions in the study area. In

the driest years (1985, 1998, 2002) average SWF is less than 10% in the VH group. There

is considerable spread in SWF values in both the VH and VL groups, however, indicating

that some areas are still close to 100% inundated in these years. Thus there are likely

areas within the study area that have more stable inundation patterns, but the grouping

analysis was not able to differentiate them. An alternative to the grouping analysis

approach could be to threshold inundation values based on expert knowledge.

Table 4.2 Total area classified in each inundation group within areas predicted to be very
poorly drained/poorly drained by disaggregated soils map. L = consistently low
inundation; VL = variable low inundation; VH = variable high inundation.

Inundation Group	L	VL	VH
Area (km^2)	31.3	6.3	4.5
% Total Area	74.3	15.0	10.7

The grouping analysis results demonstrate that the inundation maps are able to pick up

varying degrees of wetness within areas classified as very poorly/poorly drained by the

disaggregation methods. This is an indication that the inundation data could help

distinguish very poorly from poorly drained soils. Areas with consistently low SWF

values (L group) likely include poorly drained soils. Very poorly drained soils likely fall

in the VL and VH groups. Complicating factors, however include: 1) the presence of

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drainage ditches in or near many of these depressions; and 2) groundwater pumping for

irrigation has likely drawn down the regional water table over time. Current indicators of

wetness may not be reflective of the conditions under which the soils formed. Thus it is

likely that areas with low SWF values (a measure of current wetness) contain very poorly

drained soils (an indicator of historical conditions).
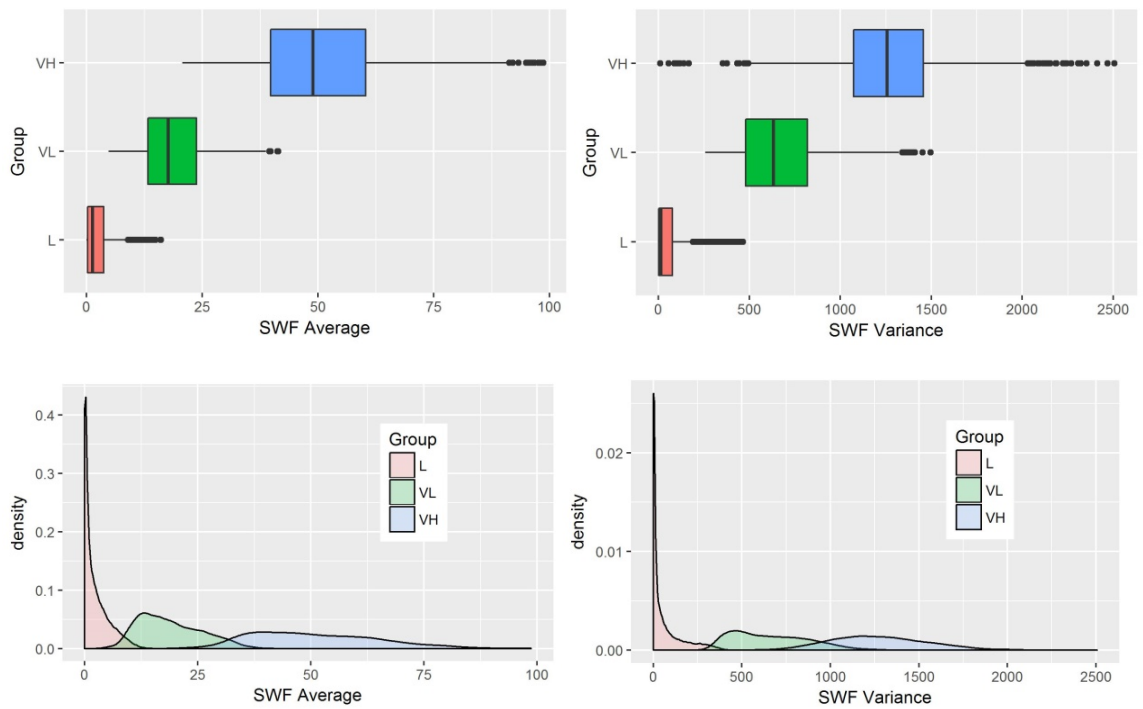
Figure 4.9 Boxplots and density plots summarizing average and variance in sub-pixel water fraction (SWF) values by group. Density plots show the smoothed distribution of values, with the peaks displaying where there is the highest concentration of values. L = consistently low inundation; VL = variable low inundation; VH = variable high inundation.
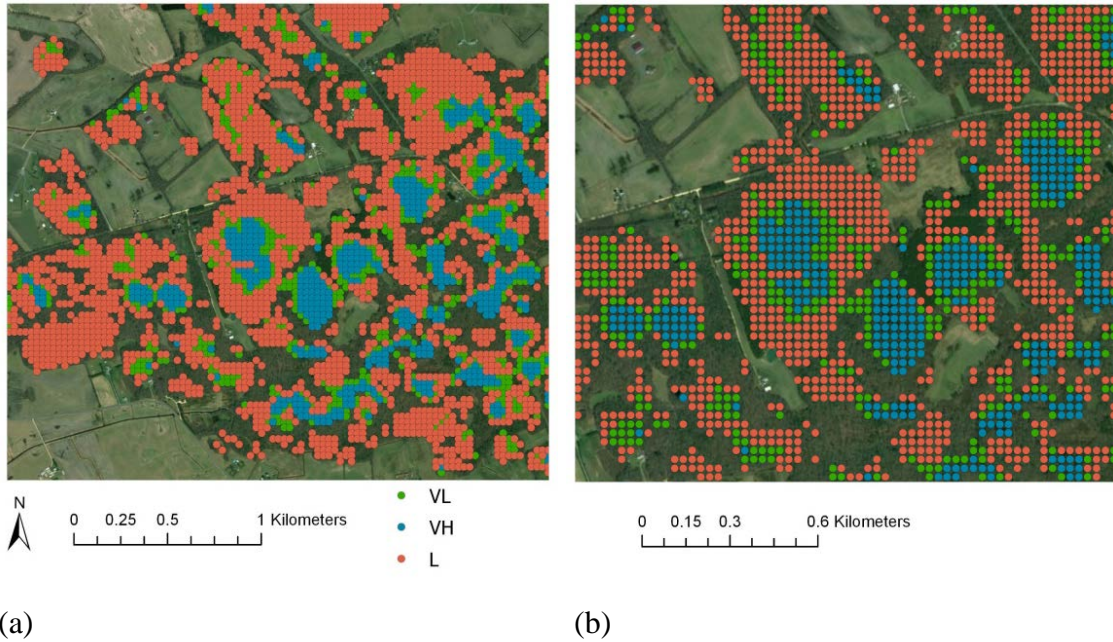
Figure 4.10 (a) Grouping analysis results in a portion of the study area in the upper Choptank River Watershed. (b) Zoomed in to several depressions. Points are located at centers of raster cells in the inundation maps. L = consistently low inundation; VL = variable low inundation; VH = variable high inundation.
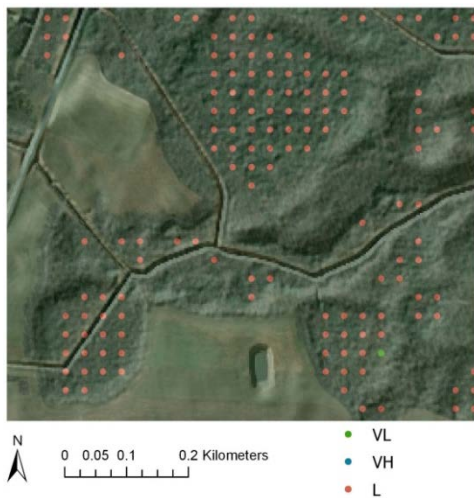
Figure 4.11 Example of drainage ditches intersecting depressions with consistently low inundation values (L group) in the upper Choptank River Watershed. Points are located at centers of raster cells in the inundation maps. L = consistently low inundation; VL = variable low inundation; VH = variable high inundation.
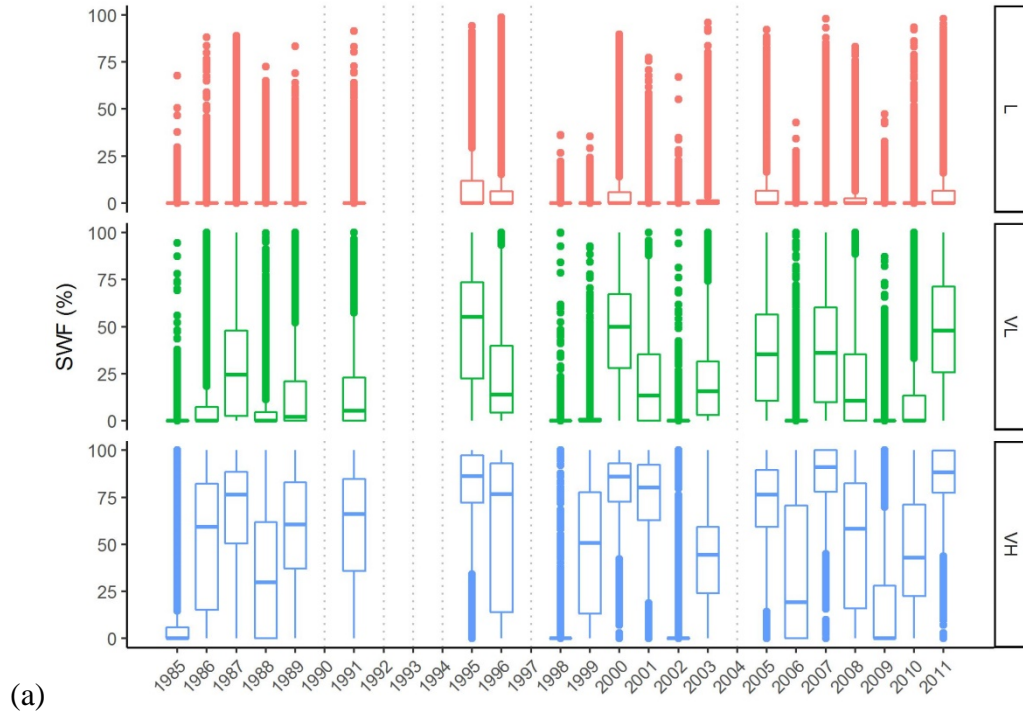
(a)
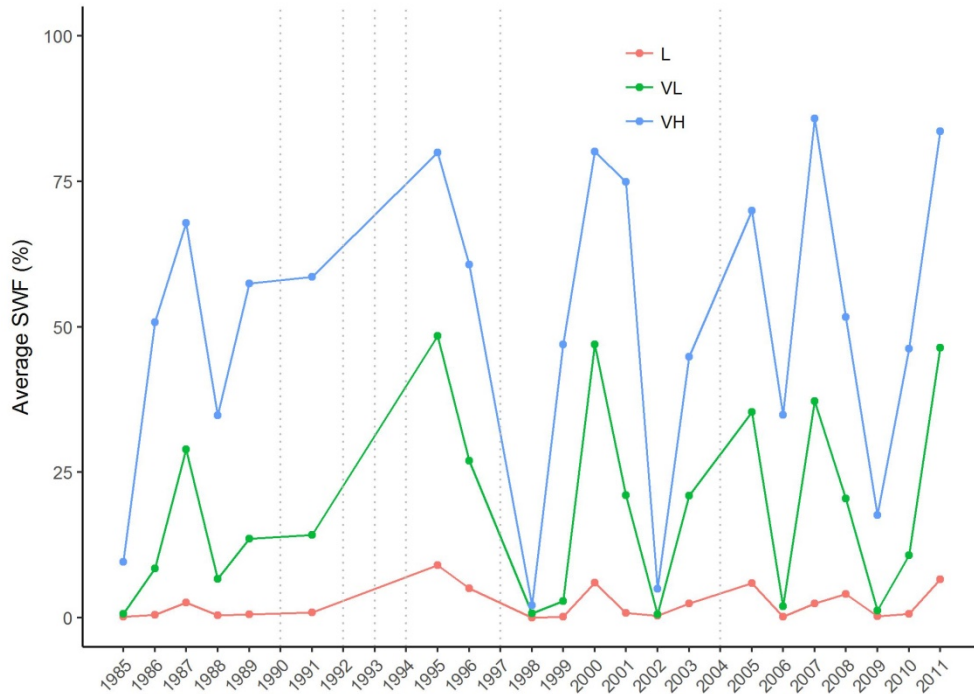
(b)

Figure 4.12 (a) Boxplots showing distributions of sub-pixel water fraction (SWF) values in each inundation group over time in the study area in the upper Choptank River Watershed. (b) Average SWF in each inundation group over time. L = consistently low inundation; VL = variable low inundation; VH = variable high inundation.

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4.3.3 Topographic metrics and inundation data

Overall distributions of topographic metrics in forested areas are displayed in Figure 4.13. Distributions of topographic metrics by inundation group are displayed in Figure 4.14. Topographic metric values in areas that were classified by the disaggregation model as VPD/PD are readily distinguished from metric values in areas with better drainage. Distributions of topographic metric values for the three inundation groups within VPD/PD areas are not as readily differentiated. Distributions show the expected trend though, with SINK and TWI values increasing and LELEV decreasing in the order L, VL, VH.

The purpose of examining the topographic metrics in relation to the inundation data was to better understand the limitations of the disaggregation methods used in Chapter 3. It is possible that despite the high resolution and accuracy of lidar, there is a limit to the predictive power of the lidar-derived topographic metrics in low-relief landscapes, especially when local hydrology has been altered through ditching and other practices. Topographic metrics, by representing landscape structure, provide a measure of potential wetness. The inundation data provide a measure of actual wetness, and are able to discern varying degrees of wetness in those areas that are potentially wet (i.e., within depressions).
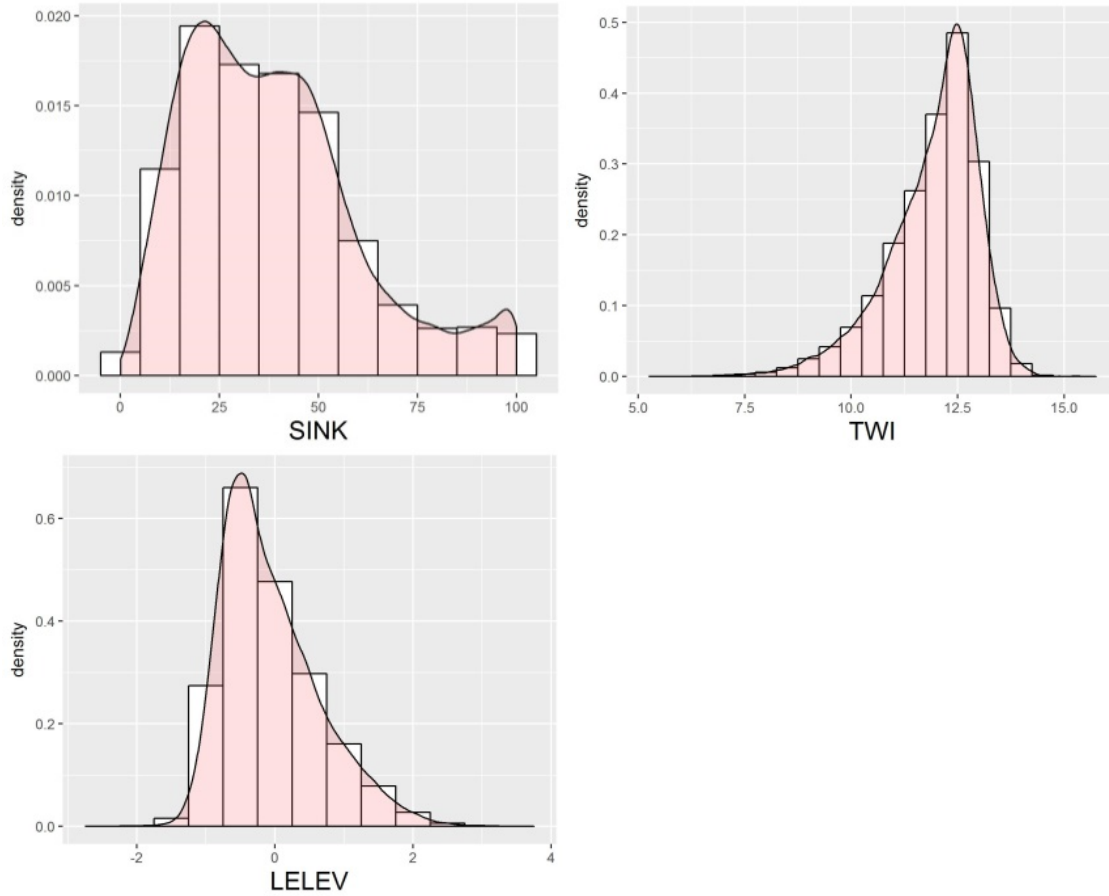
Figure 4.13 Overall distribution of topographic metric values in forested areas in study area in the Upper Choptank River Watershed. SINK (sink index) is a measure of the likelihood a raster cell is a sink – a location with no surface water outlet. TWI (topographic wetness index) is a measure of potential surface saturation based on catchment area and slope. LELEV (local elevation index) is a measure of relative topographic position within a 200 m radius.
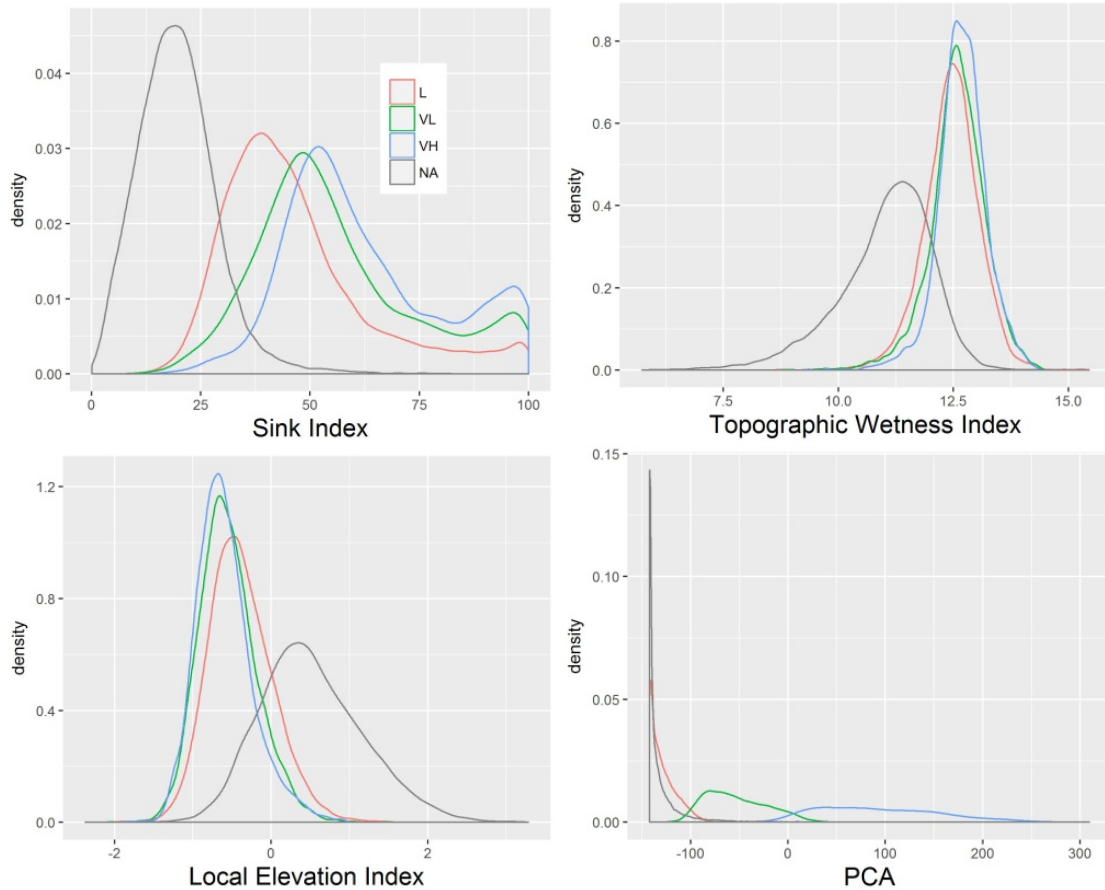
Figure 4.14 Density plots of topographic metric values and band 1 of the Principal Components Analysis (PCA) of the inundation time-series by inundation group. L = consistently low inundation; VL = variable low inundation; VH = variable high inundation. Density plots labeled NA (grey) represent data that are in better drained portions of the study area (outside of areas predicted to be very poorly drained/poorly drained areas by the disaggregated soils maps).

4.3.4 Comparison of pedon data with inundation data

The inundation data could potentially improve discernment of soil drainage classes if included as a predictor variable in the disaggregation model. To test its potential usefulness as a predictor, PCA values were extracted to points where field training pedons used in the disaggregation model were collected. Boxplots showing the

distribution of PCA values by drainage class are displayed in Figure 4.15. Pedons were

also compared with the results of the grouping analysis (Table 4.3).
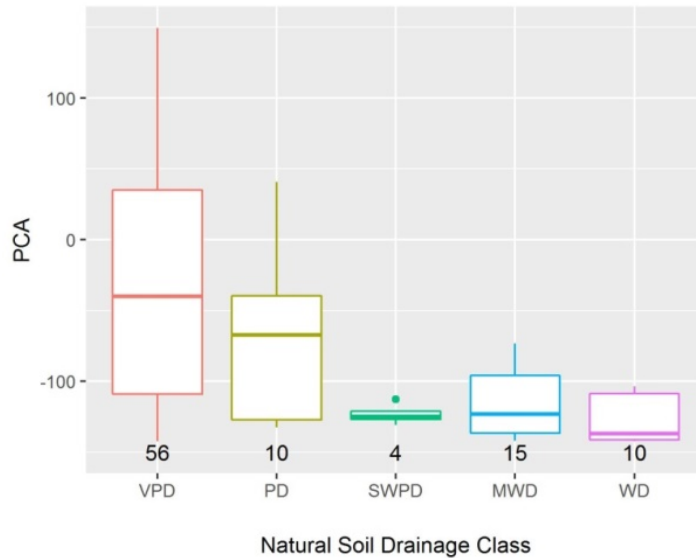
Figure 4.15 Boxplots of band 1 values of the Principal Components Analysis (PCA) of the inundation time-series by natural soil drainage class. VPD = very poorly drained; PD = poorly drained; SWPD = somewhat poorly drained; and WD = well drained. Pedons are those used as training data for the disaggregation model in Chapter 3. The number below each boxplot indicates the number of training pedons in that drainage class.

Table 4.3 Frequency table of pedon drainage class by inundation group. Inundation groups: L = consistently low inundation; VL = variable low inundation; VH = variable high inundation. Soil drainage class: VPD = very poorly drained; PD = poorly drained; SWPD = somewhat poorly drained; and WD = well drained. Only pedons located within areas classified as VPD/PD by the disaggregation model (where the grouping analysis was performed) are included.

Drainage Class	VL	VH	L
VPD	11	18	19
PD	0	2	5
SWPD	1	0	2
MWD	0	1	2
WD	0	1	0

There is a clear pattern of decreasing PCA values with increasingly better drainage, but also high variability in the PCA values. There is considerable overlap in the distributions of PCA values for VPD and PD soils. Comparison with the grouping analysis shows that the majority of PD training pedons occur in low inundation areas (L). 60% of VPD training pedons occur in VL or VH areas and 40% occur in L areas. The results indicate that although the inundation data show varying degrees of wetness within VPD/PD areas, they may not be that helpful in distinguishing VPD from PD soils. In some areas, this could be due to the presence of drainage ditches nearby, which would result in lower inundation in areas that were historically wet enough to form VPD soils. A disaggregation model incorporating the inundation data would need to account for the presence of drainage ditches, and differences in spatial scale between the lidar and inundation data.

4.4 Conclusions

A comparison of the inundation time-series maps with the disaggregated soil drainage class map within forested depressional wetlands demonstrated that the products provide complementary information on wetland location and extent in the Choptank watershed. The disaggregated soils map provides information on the extent of both inundated and saturated soils, but does not distinguish degrees of wetness well. The inundation product does not include soils that are saturated but not periodically inundated, but it does provide reliable information on wetland inundation dynamics. Because natural soil drainage class is defined by the conditions under which the soils formed, the soils map may be a better indicator of historic wetland status, whereas inundation maps may better indicate current wetland status.

The high degree of variability in year to year inundation patterns indicate that information on actual wetness derived from optical imagery from a few select dates may not improve the disaggregation model, unless those dates represented the full range of inundation conditions. The SWF maps represent a well-calibrated robust inundation time-series that may be useful in predicting soil properties, but it is unclear whether they would improve prediction of natural soil drainage class, especially in a heavily altered (e.g., ditched) landscape. A new disaggregation model incorporating the inundation data would need to account for drainage ditches, which may be the reason for consistently low inundation in some wetland depressions. A disaggregation model could be developed for un-ditched forest areas by only using training pedons in un-ditched forest areas. Establishing an appropriate ditch buffer distance to define un-ditched forest would benefit from information on the effects of ditches on inundation patterns in forested

wetlands in the study area. The training set used here was also highly imbalanced, with many more instances of VPD pedons than other classes. A new disaggregation model would benefit from a more balanced training set.

Maps of wetland extent and function are needed to guide natural-resource decision making. To address conservation issues including habitat loss and degradation, changes in species composition, changes in water quality, quantity, and flow rates, sea-level rise and coastal resilience, as well as expansion in domestic energy development, we need reliable wetlands data (U.S. Fish and Wildlife Service, 2018). in the need for critical information on wetland function has led to the augmentation of National Wetlands Inventory (NWI) maps with hydrogeomorphic attributes to create NWI+ maps (Tiner, 2010).

Products such as the SWF and disaggregated soils maps can help provide information relevant to wetland function. For example, probability maps of natural soil drainage class at the scale of individual depressions could be helpful in quantifying the extent of poorly and very poorly drained soils in hard to access forested areas, which could be useful in modeling the contribution of forested wetland complexes to downstream water quality. Natural soil drainage class can also be used to identify historic wetlands and thus opportunities for wetland restoration. It is possible that over time, the installation of drainage ditches could result in some VPD soils becoming PD due to depletion of organic carbon resulting from higher decomposition rates and lower primary productivity. VPD soils in areas with drainage ditches and consistently low inundation are likely losing organic carbon, so these areas may be good candidates for wetland restoration for carbon storage.

The addition of inundation data to digital soil mapping models could be useful in predicting other soil characteristics influenced by hydrology, such as carbon content, soil texture, and horizon thickness – factors which could influence hydrologic, biogeochemical, and habitat functions. Inundation information could also help natural resource managers characterize near-surface hydrologic connectivity that could be used, for example, to identify areas where geochemical conditions may be optimal for capturing and removing nitrate (Goldman and Needelman, 2015).

Although limited in being able to describe varying degrees of potential wetness within depressional wetlands, lidar-derived topographic metrics are important tools for mapping wetland extent and function. Topographic metrics are extremely useful in describing the structure of depressional wetland landscapes and were able to pick up variations in drainage class from rim to slope to depression. As demonstrated in Chapter 3, topographic metrics were also able to differentiate coarser textured soils on rims from finer textured soils in depressions in forest areas. Furthermore, landscape metrics, such as the number and size of wetlands, topographic wetness index and drainage density can be useful in predicting hydrologic connectivity in Delmarva bay wetland complexes (Epting et al., 2018). Hydrologic connectivity has been shown to affect water chemistry, soils, vegetation, and biota in depressional wetlands (Cook and Hauer, 2007; Snodgrass et al., 1996).

A suggested follow-up to this analysis is to quantify the accuracy of lidar-derived topographic metrics in predicting SWF and identify topographic conditions in this low-relief landscape where lidar data are no longer able to predict variations in inundation. Estimates of how potential wetness relate to actual wetness would inform operational

soils and wetland mapping by helping to quantify uncertainty in using lidar-derived topographic metrics to predict soil saturation. DSM is a new field and only recently beginning to shift from a research phase to operational use (Minasny and McBratney, 2016). DSM is typically done at low to medium resolutions, but high resolution DSM can be useful for developing maps for specific applications, such as mapping wetland soils to predict function. A better understanding of the uses and limitations of lidar-derived topographic metrics would help the field of DSM move from research to operational use.

Automated approaches to wetland mapping can greatly reduce the cost of monitoring wetlands and provide reliable information for wetland managers. With continued advancements in the acquisition of remote sensing data and increasing accessibility of complex data mining techniques, the ability to develop wetland monitoring tools at low cost will continue to improve. Model calibration based on field data and field validation will continue to be necessary to constrain uncertainty but as demonstrated by the inundation and disaggregation products, effective models can be built using a limited amount of field data.

Chapter 5 – Conclusions

Wetlands are vital in supporting clean water in the Chesapeake Bay watershed, where excess nutrients and sediment loads from human activities have contributed to a decline in water quality over the last few decades. There is great interest in restoring wetlands to mitigate excess agricultural nitrogen inputs, but efforts to develop a watershed-scale approach to planning wetland restorations have been met with considerable challenges. These include biological/physical challenges, and political/social/economic challenges. Biological/physical challenges to siting wetlands for nitrate removal include: 1) accounting for subsurface connectivity between nitrogen sources and wetlands; and 2) estimating how effective wetlands will be at removing nitrate in order to demonstrate the benefits of targeted wetland restoration and compare alternative watershed plans. Political/social/economic challenges include: 1) limited information on current wetland practices; 2) broad/unclear objectives of wetland BMPs; and 3) factors limiting landowner willingness to adopt wetland BMPs. In Chapter 2, I explored each of these challenges and proposed potential avenues of research for addressing them. The following chapters related to the first challenge, accounting for subsurface connectivity between nitrogen sources and wetlands.

On the Delmarva Peninsula, the complexity of nitrogen fate and transport complicates evaluating the effects of depressional wetlands on downstream water quality (Denver et al., 2014). In Chapter 2, I proposed three approaches to better account for subsurface N transport and enhance the implementation of wetland restoration practices 1) assessing hydrologic connectivity in areas with artificial drainage; 2) catchment-scale studies of

hydrogeomorphic predictions of hydrologic connectivity; and 2) improved use of geospatial data for predicting subsurface connectivity between N sources and wetlands.

Central to all of these is spatial information on soils and soil properties that influence and are influenced by hydrologic conditions. For example, the presence of clay-rich horizons can cause water tables to perch temporarily following rain events, promoting rapid, lateral movement of water to ditches (Vadas et al., 2007). Different hydrogeomorphic regions on the Mid-Atlantic Coastal Plain display unique groundwater flow and water quality patterns (Hamilton et al., 1993). The highest nitrate concentrations are found in groundwater beneath agricultural areas where the soils and surficial aquifer are composed of sandy, permeable sediments with little clay. The lowest groundwater nitrate concentrations are found in regions where organic matter is abundant and clay and silt deposits inhibit downward flow (Hamilton et al., 1993).

At the watershed scale, effective use of geospatial data is critical for planning wetland restorations. Developing predictions of groundwater connectivity based on landscape and soil characteristics is particularly challenging. There are several ways to improve current use of geospatial data to better identify areas where hydrology may favor N removal by wetlands. These include 1) expanded use of lidar data and topographic indices derived from lidar; 2) better use of existing soils data; 3) incorporation of ditch network data; and 4) incorporation of remote- and ground-based sensor techniques for measuring variability in soil and vegetation characteristics.

SSURGO data contain information on soil hydrologic properties to a depth of approximately 2 m, but their applications in land management planning are limited by the

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coarse scale of survey maps relative to the scale of restoration decisions, the spatial aggregation of soil components, and the difficulty in accounting for uncertainty in soil maps. Chapter 2 introduced soil survey disaggregation as a possible way to improve the use of soils data to better identify areas where hydrology and soil conditions may favor N removal by wetlands.

In Chapter 3, I developed a method for generating more spatially refined maps of natural soil drainage and texture class in a depressional wetland landscape using soil survey disaggregation techniques. The disaggregation methods developed here were unusual in that they were 1) developed for a low-relief landscape; 2) developed at high spatial resolution (3 m); 3) developed for the explicit purpose of mapping wetland soils to support wetland restoration decisions; 4) used field data for training models; 5) used SSURGO data as input variables in the models; and 6) separate models were built for forest and cropland to account for differences in expected hydrologic and depositional controls on soil properties on these lands.

The Random Forests machine learning algorithm was used to generate probability maps of drainage and texture class in forest and cropland settings in the upper part of the Choptank River watershed on central Delmarva. Predictor variables included topographic metrics derived from lidar, SSURGO data, NWI data, and agricultural ditch network data. Overall, model predictions fit our understanding of variability in natural soil drainage and texture class in forested areas, with increasingly better drainage from depression to slope to rim, and coarser textured soils on rims compared to depressions. Overall validation accuracy in the forest models was 77.1% for drainage class and 70.6% for texture class.

The development of disaggregation techniques was more challenging on cropland. This was attributed to several factors: 1) greater human modification of the landscape in cropland areas; 2) differences in the natural variation in soil properties in forest vs cropland; and 3) the nature of the training data used in forest vs cropland.

The benefits of disaggregated soils maps compared with conventional soil maps include not only greater spatial detail, but also a measure of uncertainty associated with predicted soil classes and estimates of the importance of different attributes in predicting soil classes. Measures of uncertainty in soil class predictions are important for informing land management decisions and developing models incorporating soils information. Attribute importance can help guide operational soils and wetland mapping by providing information on local landscape processes controlling soil formation and development. In forest areas, the sink index, a measure of the likelihood there is no surface water outlet at a given point in the landscape, was the best predictor of soil drainage class. Relative elevation and catchment area were the best predictors of texture class.

In Chapter 4, I conducted an exploratory data analysis comparing the disaggregated soils map with time-series inundation maps of the Delmarva developed from Landsat and lidar intensity data covering the period 1985 - 2011 (Huang et al., 2014; Jin et al., 2017). One of the limitations of the forest disaggregation model was that it was not able to differentiate very poorly from poorly drained soils. Chapter 4 explored whether the inundation data could be helpful in distinguishing these two drainage classes and attempted to identify areas with more stable vs variable inundation patterns, which could be an indication of the relative importance of specific wetland functions.

Comparison of the inundation maps with the disaggregated soils map demonstrated that the two products are complementary. Patterns in inundation corresponded well with drainage class, with highest inundation in the centers of depressions where very poorly/poorly drained soils were mapped. There were significant differences in average inundation values between VPD/PD, SWPD/MWD and WD soils.

A K means clustering algorithm was used to identify spatial variation in inundation patterns in areas mapped as VPD/PD. The cluster analysis was unable to differentiate areas with stable inundation, but it did pick up varying degrees of wetness, which in general showed a pattern of increasing inundation from the edges of depressions to the centers of depressions. In approximately 74% of the areas mapped as VPD/PD by the disaggregation methods, inundation was consistently low. In some places, entire depressions had consistently low inundation patterns. Comparison of the pedon data used to train the disaggregation model with the inundation data indicated that VPD soils could not be readily distinguished from PD soils based solely on the inundation data.

The exploratory data analysis in Chapter 4 pointed to several research directions that could inform the continued development of advanced soil and wetland mapping techniques. There is a need for better understanding of the effects of drainage ditches on indicators of current vs historic hydrologic conditions in forested depressional wetlands. A number of VPD pedons were located in areas that showed low to no inundation over the 30 year inundation time-series. Further research is needed to identify whether hydrologic conditions have changed from those under which the soils developed in these areas. If so, these sites could be good candidates for wetland restoration for carbon

storage. This is also an indication that drainage ditches should be accounted for if a new disaggregation model is built using the inundation data.

Another area of research identified in Chapter 4 is to further explore the relationships between the topographic metrics (a measure of potential wetness) and the inundation data (a measure of actual wetness). Quantification of this relationship in not only depressional wetlands but also riparian wetlands and wetland flats could inform the development of operational soils and wetland mapping methods by providing a measure of uncertainty in using the topographic metrics to predict saturation and inundation.

Appendix A: Supplemental Materials for Chapter 3

Supplemental Table 3.1 NRCS soil mapping model for Caroline County, MD. Courtesy of Jim Brewer.

Water Table Depth (Redox Features)	Fine-silty SiL/SiCL Bt	Fine-silty (>50" silts)	Fine-loamy SL/L surface SCL Bt	Fine-loamy SiL surface SiL/L Bt	Coarse-loamy LS/SL surface SL Bt	Coarse-loamy L surface L/SL Bt	Sandy (w/ Bt) LS Bt	Sandy (w/o Bt)
>72" W	Matapeake		Sassafras	Reybold	Downer	Greenwich	Galestown	Evesboro
40-72" SWWD	Nassawango		Hambrook	Queponco	Ingleside	Unicorn	Cedartown	Runclint
20-40" MW	Mattapex	Leipsic	Woodstown	Manokin	Hammonton	Pineyneck		Galloway
	Butlertown							
10-20" SWP	Crosiadore		Marshyhope	Annemessex	Glassboro			Klej
0-10" P	Othello	Tent	Fallsington	Quindocqua	Hurlock	Carmichael		Askecksy
	Elkton			Blackiston				
	Whitemarsh							
ponded to 0" VP	Kentuck		Corsica		Pone			

Supplemental Table 3.1 (contined) NRCS soil mapping model for Caroline County, MD. Courtesy of Jim Brewer.

Water Table Depth (Redox Features)	Fine SiCL/SiC/C Bt	Arenic SL Bt	Paleudults arenic/gross	Other (no drainage order)	Coarse-loamy (no Bt)	Coarse-loamy (3" to 6" Bt)	Sandy w/ Bh
>72" W		Fort Mott	Henlopen	Udorthents, refuse Udorthents, borrow			
40-72" SWWD		Rosedale		Udorthents			
20-40" MW	Keyport	Rockawalkin	Pepperbox	Beaches			
10-20" SWP							
0-10" P	Lenni						
ponded to 0" VP					Mullica		Berryland

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Supplemental Table 3.2. Training point accuracy of texture group predictions in cropland areas: a) with map unit covariates (overall training accuracy 74.9%); b) without map unit covariates (overall training accuracy 73.8%).

(a)

	Reference	
	Coarse	Fine
Coarse	15	13
Fine	36	131
Class error	0.71	0.09

(b)

	Reference	
	Coarse	Fine
Coarse	12	12
Fine	39	132
Class error	0.76	0.08

Supplemental Table 3.3. Validation point accuracy of texture group predictions in cropland areas: a) with map unit covariates (overall accuracy 43.1%, $\kappa = -0.11$); b) without map unit covariates (overall accuracy 45.8%, $\kappa = -0.06$).

(a)

	Reference		
	Coarse	Fine	User's Accuracy
Coarse	0	4	0.0%
Fine	37	31	45.6%
Producer's Accuracy	0.0%	88.6%	

(b)

	Reference		
	Coarse	Fine	User's Accuracy
Coarse	1	3	25.0%
Fine	36	32	47.1%
Producer's Accuracy	2.7%	91.4%	
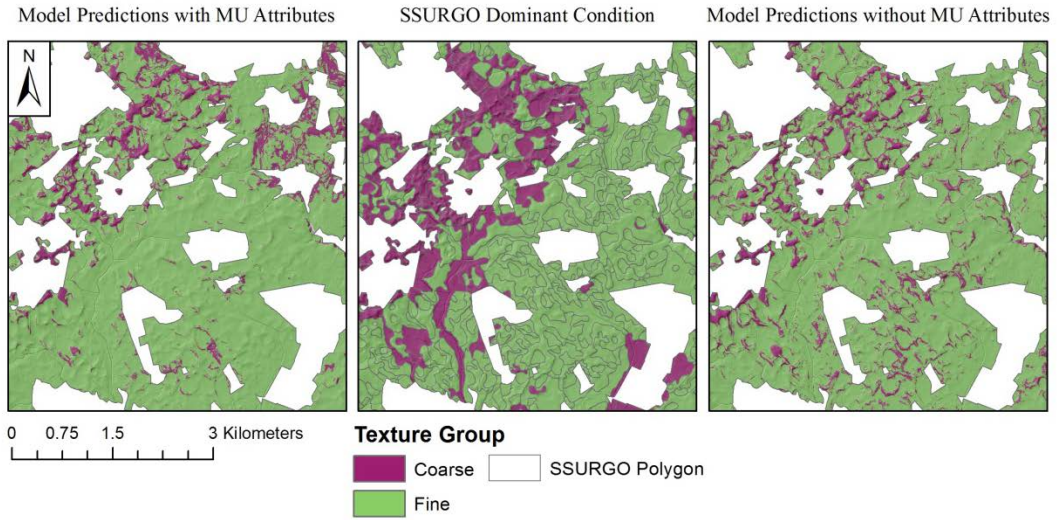
Supplemental Figure 3.1. Soil texture group predictions and SSURGO particle size class (dominant condition) in cropland areas.
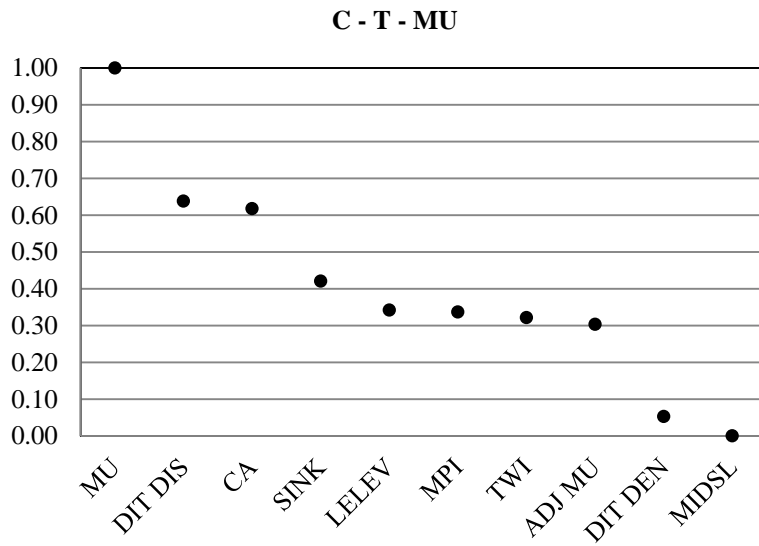
(a)
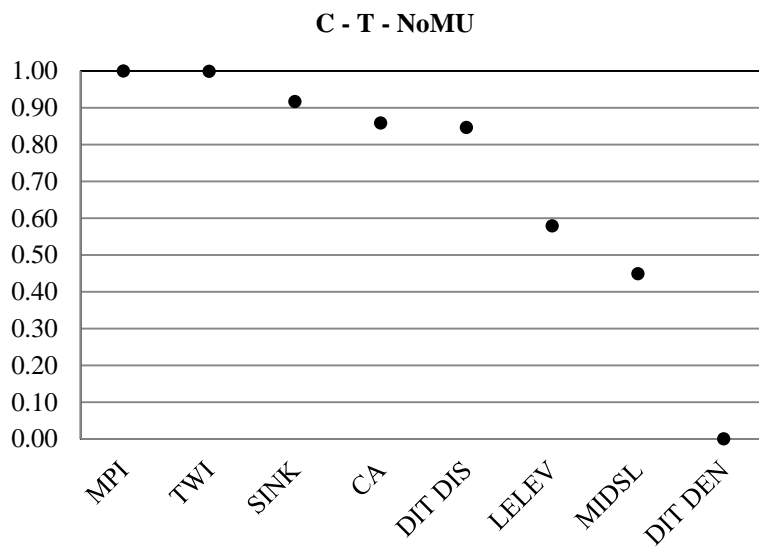
(b)

Supplemental Figure 3.2 Relative importance of variables in predicting texture group in cropland areas: a) with map units; b) without map units.
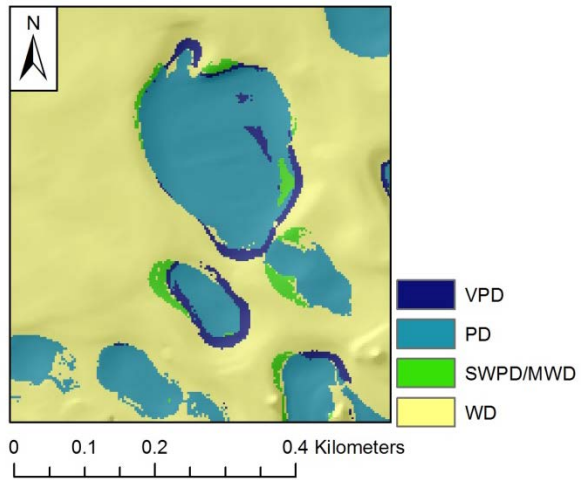
Supplemental Figure 3.3. Example of cropland area where VPD soils were mapped along the edges of depressions and PD soils in the center.

Appendix B: Validation Pedon Descriptions

Site: MD 6A depression inner   **Described:** M. Goldman, C. Seitz 4/2/2015
Landcover: Forest   **Water Table:** Ponded to 6 cm
Drainage Class: VPD   **Texture Group:** Coarse

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
Oe	9			2.5YR 2.5/2			
A	47	LS	8	10YR 2/2			
EAg	61	LS	7	10YR 6/1			
Eg	83	S	3	10YR 7/1			
Btg	91	SCL	21	10YR 4/1			
CBg	97	SL	10	10YR 4/1			

Site: MD 6B depression outer   **Described:** M. Goldman, C. Seitz 9/3/2015
Landcover: Forest   **Water Table:** 10 cm
Drainage Class: VPD   **Texture Group:** Coarse

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
Oe	11			2/5YR 2.5/2			
A1	54	LS (SL)	6	10YR 2/2			
A2	74	LS	7	10YR 2/2			
Bg	80	S	4	10YR 5/1			
Btg1	89	SL	19	10YR 6/1	20% D		
Btg2	106	SCL	26	5Y 6/1	1% D		

Site: MD 6C slope   **Described:** M. Goldman, C. Seitz 9/3/2015
Landcover: Forest   **Water Table:** Not recorded
Drainage Class: PD   **Texture Group:** Coarse

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
Oe	7			2.5YR 2.5/2			
A1	12	SL	8	5YR 2.5/1			
AE (EA?)	27	SL (LS?)	3	2.5Y 3/1			
Eg (E?)	80	SL (LS?)	2	2.5Y 5/1			
Bg		LS	9	2.5Y 4/1			

Site: MD 6D rim   **Described:** M. Goldman, C. Seitz 9/3/2015
Landcover: Forest   **Water Table:** 67 cm
Drainage Class: WD   **Texture Group:** Coarse

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
Oe	5			2.5YR 2.5/2			
A	10	S	4	2.5Y 3/1			
Bw1	21	S	4	10YR 4/4			
Bw2	44	LS	6	7.5YR 4/4			Spodic properties?
Bw3	54	LS	6	7.5YR 3/4			
	63	LS	5	7.5YR 2.5/2			
	80	LS	5	2.5YR 2.5/2			
Ab	96	LS (S)	4	10YR 2/2			
	101	LS	8	10YR 4/3			

Site: MD 2A depression outer   **Described:** M. Goldman, C. Seitz 4/9/2015
Landcover: Forest   **Water Table:** 7 cm
Drainage Class: VPD   **Texture Group:** Coarse

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
Oe	10			2.5YR 2.5/2			
A1	50	LS	8	10YR 2/1			
A2	73	LS	7	10YR 3/1		15% D 2.5Y 5/2 at 65 cm	
Bg	92	LS	6	10YR 4/2			
CB	100	S	2	10YR 5/3			

Site: MD 2B slope   **Described:** M. Goldman, C. Seitz 4/9/2015
Landcover: Forest   **Water Table:** 26 cm
Drainage Class: VPD   **Texture Group:** Coarse

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
Oe	10			2.5YR 2.5/2			
A1	50	LS	8	10YR 2/1			
A2	73	LS	7	10YR 3/1		15% D 2.5Y 5/2 at 65 cm	
Bg	92	LS	6	10YR 4/2			
CB	100	S	2	10YR 5/3			

Site: MD 2C rim

Landcover: Forest

Drainage Class: SWPD

Described: M. Goldman, C. Seitz 4/9/2015

Water Table: 50 cm

Texture Group: Coarse

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
Oe	14			2.5YR 2.5/2			
AE	20	LS	10	10YR 2/1			uncoated sand grains
	33	LS	9	10YR 3/2			
Bg	54	SL	12	2.5Y 6/1	25% D		
Btg	71	SL	16	5Y 6/1	1% D		
CBg	82	S	2	2.5Y 6/1	5% D		
Cg	103	S	2	2.5Y 6/2	7% D		
C	112	S	1	2.5Y 6/3	40% D		

Site: MD 3A depression inner   **Described:** M. Goldman, C. Seitz 4/9/2015
Landcover: Forest   **Water Table:** not recorded
Drainage Class: VPD   **Texture Group:** Coarse

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
Oe	13			2.5YR 2.5/2			
A	53	LS	8	10YR 2/1			
AB	91	LS	7	10YR 3/2			
Bg	100	S	2	10YR 4/2			

Site: MD 3B slope   **Described:** M. Goldman, C. Seitz 4/9/2015
Landcover: Forest   **Water Table:** 43 cm
Drainage Class: VPD   **Texture Group:** Coarse

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	
Oe	8			2.5YR 2.5/2			
A	38	SL	8	10YR 2/1			
AB	50	SL	7	10YR 4/2			
Bg	59	S	5	10YR 6/1	1% D		
Btg1	73	SL	12	5Y 6/2	15% D		
Btg2	85	SL	11	5Y 6/2	35% D		
BCg	94	S	3	2.5Y 6/2	1% D		small gravels
Cg	104	S	2	2.5Y 7/1			small gravels

Site: MD 3C rim   **Described:** M. Goldman, C. Seitz 4/9/2015
Landcover: Forest   **Water Table:** 60 cm
Drainage Class: MWD   **Texture Group:** Coarse

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
Oe	14			2.5YR 2.5/2			
AE	32	LS	8	10YR 2/1			uncoated sand grains
AB	43	LS	7	10YR 3/2			
BC	73	LS	7	10YR 5/3			gravel @ 57 cm
CB	87	S	4	2.5Y 5/3			
Cg	104	LS	6	2.5Y 6/2	8% D		

Site: SNS 19A depression inner   **Described:** M. Goldman, C. Seitz 4/12/2015
Landcover: Forest   **Water Table:** ponded to 48 cm
Drainage Class: VPD   **Texture Group:**

Comments: Root mat followed by muck. High clay, high OM surface. At 56 cm mucky SiCL, concentrations (35%), depletions. At 77 cm, concentrations drop to 20%, no depletions. At 80 cm, prominent concentrations, sand increase, clay decrease, matrix lightens.

Site: SNS 19B depression outer   **Described:** M. Goldman, C. Seitz 4/12/2015
Landcover: Forest   **Water Table:** ponded to 4 cm
Drainage Class: VPD   **Texture Group:** Coarse

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
Oe	13			5YR 2.5/2			
A	44	mucky SL	9	10YR 2/1			
Bg	56	SL	11	2.5Y 5/1	4% D		
Btg1	76	SL	18	2.5Y 5/1	35% D		
Btg2	92	SCL	22	2.5Y 5/1	8% D 2% P		
Btg3	105	SCL	30	2.5Y 5/1	4% D		

Site: SNS 19C slope   **Described:** M. Goldman, C. Seitz 4/12/2015
Landcover: Forest   **Water Table:** 25 cm
Drainage Class: PD   **Texture Group:** Coarse

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
Oe	8			2.5YR 2.5/2			
A	24	LS	8	10YR 2/1			
Bg1	55	S	2	2.5Y 5/2			
Bg2	65	S	2	2.5Y 6/2			
Bg3	100	S	1	2.5Y 4/2			

Site: SNS 19D rim   **Described:** M. Goldman, C. Seitz 4/12/2015
Landcover: Forest   **Water Table:** 93 cm
Drainage Class: MWD   **Texture Group:** Coarse

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
Oe	13			2.5YR 2.5/2			
A1	21	LS	5	10YR 2/1			
A2	24	LS	5	10YR 3/2			
BA	49	SL	8	10YR 4/4			Small gravels
Bw	67	SL	9	2.5Y 5/4	5% F	1% D	
Bg1	82	LS	5	2.5Y 6/1	20% D (3% P)		
Btg	91	LS	12	5Y 6/1	25% D (5% P)		
C	107	S	2	2.5Y 6/3	20% D (3% P)		

Site: SNS 9A depression inner   **Described:** M. Goldman, C. Seitz 4/12/2015
Landcover: Forest   **Water Table:** ponded to 55 cm
Drainage Class: VPD   **Texture Group:**

Comments: Organic surface. A horizon to 67 cm. SiL/L. Depleted matrix at 75 cm.

Site: SNS 9B depression outer   **Described:** M. Goldman, C. Seitz 4/12/2015
Landcover: Forest   **Water Table:** 3 cm
Drainage Class: VPD   **Texture Group:** Coarse

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
Oe	16			2.5YR 2.5/2			
A1	50	Mucky LS	5	10YR 2/1			
A2	73	LS	7	10YR 2/2			
Abg	90	LS	5	10YR 4/2		13% D	
Bg	103	LS	5	5Y 6/2	1% F		

Site: SNS 9C slope   **Described:** M. Goldman, C. Seitz 4/12/2015
Landcover: Forest   **Water Table:** 26 cm
Drainage Class: VPD   **Texture Group:** Coarse

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
Oe	11			2.5YR 2.5/2			
A	36	LS	6	10YR 2/1			
Bg	53	S	6	10YR 4/2			
Ab?	70	LS	7	10YR 2/2	3% D	1% 10YR 4/2	
Cg	84	SL	10	2.5Y 5/2	7% D		

Site: SNS 9D rim   **Described:** M. Goldman, C. Seitz 4/12/2015
Landcover: Forest   **Water Table:** not reached
Drainage Class: WD   **Texture Group:** Coarse

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
Oe	9			2.5YR 2.5/2			
A	13	LS	7	10YR 2/1			
Bw1	83	S	2	10YR 5/6			
Bw2	100	S	1	10YR 5/6	25% D		

Site: SNS 11A depression inner   **Described:** M. Goldman, C. Seitz 4/21/2015
Landcover: Forest   **Water Table:** ponded to 2 cm
Drainage Class: VPD   **Texture Group:** Coarse

Comments:

Horizon	Depth	Texture	Comments
A	31	LS	Mucky surface ~6 cm
	60	LS	Darker
	74	LS	Reddish Brown
	100	LS	spodic properties

Site: SNS 11B depression outer   **Described:** M. Goldman, C. Seitz 4/21/2015
Landcover: Forest   **Water Table:** 4 cm
Drainage Class: VPD   **Texture Group:** Coarse

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comment
Oe	3			2.5YR 2.5/2			
A1	23	LS	11	7.5YR 2.5/1			
	38	LS	7	10YR 3/2			
	62	LS	8	7.5YR 3/3			Bsh or organic staining?
	82	SL	10	10YR 4/3			
	100	SL	6	7.5YR 3/4			

Site: SNS 11C slope   **Described:** M. Goldman, C. Seitz 4/21/2015
Landcover: Forest   **Water Table:** 44 cm
Drainage Class: SWPD   **Texture Group:** Coarse

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
Oe	5			2.5YR 2.5/2			
AE	13	SL	9	10YR 2/2			60% grains coated
Bt1	46	SL	12	10YR 4/4		5% 10YR 6/2 starts at 44 cm	
Bt2	81	SL	16	10YR 5/3	10% D, 2% P	20% 10YR 6/1	3% chert
BC	100	LS	4	10YR 5/3		30% 10YR 6/1	4% chert

Site: SNS 11D rim   **Described:** M. Goldman, C. Seitz 4/21/2015
Landcover: Forest   **Water Table:** not recorded
Drainage Class: WD   **Texture Group:** Coarse

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
Oe (i)	9	root mat		2.5YR 2.5/2			
A1	11	SL	10	2.5YR 2.5/1			
A2	14	SL	10	10YR 2/2			
Bw1	69	LS	6	10YR 4/4			
Bw2	95	LS	4	10YR 4/6			
Bw3	103	SL	3	10YR 4/6			

Site: DEA 4A depression center   **Described:** M. Goldman, K. Rankin 6/12/2015
Landcover: Forest   **Water Table:** 18 cm
Drainage Class: VPD   **Texture Group:** Fine

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
Oe	4			10YR 2/2			
A	6	SiL	11	2.5Y 2.5/1			
Btg1	30	SiCL	28	2.5Y 6/1	25% P		
Btg2	36	SiC	44	2.5Y 6/1	25% P		
Btg3	44	SiC	48	2.5Y 6/1	25% P		
BCtg	58	C	55	5Y 6/1	35% P		

Site: DEA 4B depression outer   **Described:** M. Goldman, K. Rankin 6/12/2015
Landcover: Forest   **Water Table:** 97 cm
Drainage Class: PD   **Texture Group:** Fine

Comments

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
Oe	2			10YR 2/2			
A	6	SiL	12	10YR 2/2			
Btg1	13	SiL	16	2.5Y 5/1			
Btg3	20	SiL	23	2.5Y 6/1	15% D		
Btg4	32	SiL	25	2.5Y 6/1	25% P		
Btg5	54	SiCL	38	2.5Y 5/1	30% P		
BCg1	75	SiCL	35	5Y 5/1	25% P		
BCg2	100	SiCL	36	5Y 6/1	25% P		

Site: DEA 4C slope
Landcover: Forest
Drainage Class: MWD

Described: M. Goldman, K. Rankin 6/12/2015
Water Table: not recorded
Texture Group: Fine

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
A	7	SiL	12	10YR 2/2			
Bt1	46	L	23	2.5Y 5/4			
Bt2	62	L	26	10YR 5/6			
Bt3	72	L	26	10YR 5/6		2% 2.5Y 6/2	
Bt4	106	L	24	10YR 5/6	30% D	5% 10YR 6/1	

Site: DEA 4D rim
Landcover: Forest
Drainage Class: WD

Described: M. Goldman, K. Rankin 6/12/2015
Water Table: not recorded
Texture Group: Coarse

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
A	11	L	12	10YR 2/2			
Bt1	42	L	17	2.5Y 5/3			
Bt2	56	L	24	10YR 5/4			
Bt3	68	L	26	10YR 5/6			
BC	81	SL	16	7.5YR 5/6	35% D		
C	107	S	3	10YR 5/6	35% D		gets yellower at 94, some chert at bottom

Site: DEA 3A depression inner
Landcover: Forest
Drainage Class: PD

Described: M. Goldman, K. Rankin 6/19/2015
Water Table: not recorded
Texture Group: Fine

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
Oe	8			7.5YR 2.5/2			
A1	13	SiL	13	10YR 2/1			
A2	19	SiL	15	10YR 3/2			
Btg1	28	L	25	10YR 5/1	20% P		
Btg2	54	L	26	10YR 5/1	25% P		
BCg	66	SCL	21	10YR 5/1	20% P		
	103	SC	38	2.5Y 5/2	15% D		

Site: DEA 3B depression outer
Landcover: Forest
Drainage Class: SWPD

Described: M. Goldman, K. Rankin 6/19/2015
Water Table: not recorded
Texture Group: Fine

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
Oe	6			7.5YR 2.5/2			
A	18	SiL	11	10YR 3/2			darker top 3 cm
AB	32	L (border SiL)	11	2.5Y 5/3			
Bt1	45	L (border SL)	24	2.5Y 6/3	15% D (5% P)		
Bt2	55	L (border SL)	26	2.5Y 5/3	35% P	5% 2.5Y 6/1	
Btg	78	L (border SiL)	26	2.5Y 5/2	30% P		
BCg1	96	L (border SiL)	25	5Y 6/1	20% P		
BCg2	108	SiL (border L)	26	5Y 6/1	10% P		

Site: DEA 3C slope   **Described:** M. Goldman, K. Rankin 6/19/2015
Landcover: Forest   **Water Table:** not recorded
Drainage Class: WD   **Texture Group:** Coarse

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
A1	6	L	12	10YR 2/2			
A2	13	SiL	9	10YR 3/3			
Bw1	53	LS	5	2.5Y 5/4			
Bw2	67	LS	6	2.5Y 6/4	5% D		
Bw3	100	LS	9	2.5Y 6/4	5% D		spodic-like concentrations of OM+Fe

Site: DEA 3D rim   **Described:** M. Goldman, K. Rankin 6/19/2015
Landcover: Forest   **Water Table:** not recorded
Drainage Class: WD   **Texture Group:** Coarse

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
Oe	3			10YR 2/2			
A	12	SiL	12	10YR 2/2			
Bt1	36	L	17	10YR 5/4			
Bt2	107	L	16	7.5YR 5/6			

Site: DEA 5A depression inner   **Described:** M. Goldman, K. Rankin 6/30/2015
Landcover: Forest   **Water Table:** ponded to 2 cm
Drainage Class: PD   **Texture Group:** Fine

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
Oe	1						
A	13	SiL	12	10YR 3/2			
Btg1	22	L	23	5Y 6/1			
Btg2	33	L	26	5Y 6/1	20% D along roots		
Btg3	62	SiCL	34	2.5Y 5/1	35% P		
Btg4	72	C	48	2.5Y 6/1	25% D and P		
Btg5	105	CL	35	5Y 6/1	15% D (5% P)		

Site: DEA 5B depression inner   **Described:** M. Goldman, K. Rankin 6/30/2015
Landcover: Forest   **Water Table:** 70 cm
Drainage Class: PD   **Texture Group:** Fine

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
Oe	6			10YR 2/2			
A	10	L	11	10YR 3/2			
	19	L	14	2.5Y 5/2			BA or B/A
	31	L	18	5Y 6/1	15% D (2% P)		
	43	L	24	5Y 6/1	20% D and P		
	52	SiC	43	2.5Y 5/1	45% P		
	60	SiCL	31	5Y 6/1	25% P		
	74	CL	33	5Y 6/1	25% P		
	103	CL	29	5Y 6/1	25% P		
	105			5Y 6/1	10% D/P		

Site: DEA 5C slope   **Described:** M. Goldman, K. Rankin 6/30/2015
Landcover: Forest   **Water Table:** 99 cm
Drainage Class: PD   **Texture Group:** Coarse

Comments: SWPD

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
Oe	6			7.5YR 3/2			
A	15	SL	12	10YR 3/2			
B/A	36	SL	10	2.5Y 5/2			B/A
	49	SL	12	10YR 4/2			
	62	SL	15	2.5Y 5/2	2% D at bottom		
	80	SL	17	2.5Y 6/2	5% D		
	94	SCL	22	2.5Y 6/1	35% P		
	104	SL	19	2.5Y 6/1	20% P		
	110	SL	12	2.5Y 6/1	40% P		

Site: DEA 5D rim   **Described:** M. Goldman, K. Rankin 6/30/2015
Landcover: Forest   **Water Table:** 102 cm
Drainage Class: MWD   **Texture Group:** Fine

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
Oe	5			5YR 2.5/1			
A	8	SiL	11	7.5YR 2.5/1			
B	25	L	13	2.5Y 5/4			
Bt1	38	L	17	2.5Y 6/4			
Bt2	50	L	24	2.5Y 5/6			
Bt3	68	L	26	2.5Y 5/6	20% D	5% 2.5Y 6/3	
Bt4	81	CL	28	2.5Y 6/4	25% D	25% 2.5Y 6/1	
BCg	102	L	25	2.5Y 6/1	35% P		
Cg	110	SL	12	2.5Y 6/1	30% P		

Site: BJF 11A depression inner   **Described:** M. Goldman, C. Seitz 5/25/2015
Landcover: Forest   **Water Table:** ponded to 6 cm
Drainage Class: VPD   **Texture Group:** Fine

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
Oe	8	matted vegetation		5YR 2.5/1			
A	20	L	9	10YR 3/2			
Btg1	46	L	16	10YR 5/1			
Btg2	62	L	16	5Y 6/1			
Btg3	92	L	26	5Y 6/1	25% P		5% beaverdam chert
BCg	110	SCL	20	5Y 6/1			7% chert, small gravels

Site: BJF 11B depression outer   **Described:** M. Goldman, C. Seitz 5/25/2015
Landcover: Forest   **Water Table:** 5 cm
Drainage Class: PD   **Texture Group:** Fine

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
Oe	6			2.5YR 2.5/1			
A	20	L	6	10YR 4/1			
Btg1	40	L	20	10YR 5/1			
Btg2	70	CL	32	10YR 5/1	10% P		
BCg	99	SCL	23	2.5Y 5/1	10% P		
Cg	106	SCL	20	2.5Y 5/1	10% P		

Site: BJF 11C slope   **Described:** M. Goldman, C. Seitz 5/25/2015
Landcover: Forest   **Water Table:** 17 cm
Drainage Class: PD   **Texture Group:** Fine

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
Oe	14			2.5YR 2.5/2			
A	22	L	5	10YR 2/2			
Btg1	34	L	20	2.5Y 5/1			
Btg2	54	L	22	2.5Y 5/1	5% P		
Btg3	86	CL	32	2.5Y 5/1	15% P		3% chert
Cg1	100	SCL	24	2.5Y 6/1			7% gravels
Cg2	111	SCL	20	2.5Y 6/1	10% P		7% gravels

Site: BJF 11D rim   **Described:** M. Goldman, C. Seitz 5/25/2015
Landcover: Forest   **Water Table:** not recorded
Drainage Class: MWD   **Texture Group:** Fine

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
Oe	3			2.5YR 2.5/2			
A	7	L	8	10YR 2/2			
	31	L	12	10YR 4/4			
	51	SL	10	10YR 5/4			12% gravels
	69	SL	12	10YR 5/6	10% D		4% gravels
	80	CL	28	10YR 5/6	30% P		
	103	SiCL	34	5Y 6/1	40% P		

Site: BJF 28A depression inner   **Described:** Maggie Goldman, Chris Seitz 5/25/2015
Landcover: Forest   **Water Table:** ponded to 4 cm
Drainage Class: VPD   **Texture Group:** Coarse

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
Oe	10			5YR 2.5/2			
A	31	L	7	10YR 2/1			
AB	45	SiL	10	10YR 3/2			
Btg1	69	SiL	18	10YR 4/1	25% P		
Btg2	85	SiL	16	2.5Y 5/1	15% P		
Cg	92	SL	12	10YR 4/1	10% P		

Site: BJF 28B depression outer   **Described:** M. Goldman, C. Seitz 5/25/2015
Landcover: Forest   **Water Table:** 2 cm
Drainage Class: VPD   **Texture Group:** Coarse

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
Oe	10			2.5YR 2.5/2			
A	31	SL	7	10YR 2/1			
Btg1	42	L	17	10YR 4/1			
Btg2	72	L	16	2.5Y 5/1	5% P		
Btg3	89	L	16	2.5Y 5/1			
BCg	95	SL	12	2.5Y 5/1			

Site: BJF 28C slope   **Described:** M. Goldman, C. Seitz 5/25/2015
Landcover: Forest   **Water Table:** ~16 cm
Drainage Class: VPD   **Texture Group:** Coarse

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.
Oe	15			2.5YR 2.5/2		
A	35	SL	6	10YR 2/1		
	48	SiL	11	10YR 3/1	5% P	
	62	SiL	15	10YR 4/1	20% P	
	76	SiL	18	10YR 4/1	20% P	5% 10YR 5/1
	90	CL	28	2.5Y 6/1	15% P	
	96	SCL	34	2.5Y 6/1		

Site: BJF 28D rim   **Described:** M. Goldman, C. Seitz 5/25/2015
Landcover: Forest   **Water Table:** 70 cm
Drainage Class: SWPD   **Texture Group:** Coarse

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
Oe	8			2.5YR 2.5/2			
A	12	SL	5	10YR 2/1			
Bw	35	SL	8	10YR 5/3	15% P		
Bg	60	SL	10	2.5Y 6/2	25% P		
Cg1	77	SL	14	5Y 6/1	25% P		
Cg2	101	SL	17	5Y 6/1	25% P		

Site: BJF 10A depression inner **Described:** M. Goldman, K. Rankin 6/29/2015
Landcover: Forest **Water Table:** not recorded
Drainage Class: VPD **Texture Group:** Coarse

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
Oe	8			7.5YR 2.5/1			large flat depression
A	29	L	14	7.5YR 3/1		1% 10YR 4/1	rims defined by ag field and road
	53	L	13	7.5YR 4/1		1% 7.5YR 5/1	slope not apparent in field
	66	L	11	7.5YR 4/1			
	73	SL	18	10YR 5/1			
	82	SL	16	2.5YR 6/1			
	91	SCL	22	2.5YR 6/1	5% P		
	98	SCL	22	2.5YR 6/1	10% P		
	105	SL	18	2.5YR 6/1	5% P		

Site: BJF 10B depression outer **Described:** M. Goldman, K. Rankin 6/29/2015
Landcover: Forest **Water Table:** 24 cm
Drainage Class: VPD **Texture Group:** Fine

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
Oe	8			7.5YR 2.5/2			
A	29	SiL	15	7.5YR 2.5/1		1% 10YR 4/1	
Btg1	50	SiL	26	10YR 4/1	2% D starting at 44		shell fragments beginning in A, pick up in bottom horizon
Btg2	92	CL	35	2.5Y 6/1	25% P		
CBg	105	SL	18	5Y 6/1	2% P		10% coarse frags

Site: BJF 10C slope
Landcover: Forest
Drainage Class: PD

Described: M. Goldman, K. Rankin 6/29/2015
Water Table: 42 cm, saturated throughout
Texture Group: Coarse

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
Oe	8			5YR 2.5/1			
A	21	SL	13	7.5YR 2.5/1			
	41	SL	14	10YR 3/2		5% 10YR 4/2	
	55	SL	14	10YR 5/2			
	62	SL	18	2.5Y 6/2	3% D		
	95	SL	16	5Y 6/1	15% P starting @ 87		
	100	LS	6	2.5Y 6/1	15% P		

Site: BJF 10D rim **Described:** M. Goldman, K. Rankin 6/29/2015
Landcover: Forest **Water Table:** 74 cm
Drainage Class: MWD **Texture Group:** Coarse

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
Oe	8			7.5YR 2.5/1			
A	19	SL	10	7.5YR 2.5/1 and 7.5YR 3/2 @ 16 cm			
	36	SL	12	10YR 4/3	10% D along roots	10% 10YR 4/2, 2% 5/2	buried A?
	44	SL	11	10YR 3/2	2% D		
	52	SL	12	10YR 4/3	5% D	2% 2.5Y 5/2	
	61	SL	15	2.5Y 6/2			
	71	LS	10	2.5Y 6/2(1)			
	81	LS	8	5Y 6/1	35% P		
	92	SL (almost SCL)	19	5Y 6/1	35% P		clay jump
	105	SL (almost SCL)	19	5Y 6/1	20% P		

Site: SDI 3A depression inner   **Described:** M. Goldman, K. Rankin 7/13/2015
Landcover: Forest   **Water Table:** not reached
Drainage Class: VPD   **Texture Group:** Fine

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
Oe	11			2.5YR 2.5/2			
A	20	SiL	14	10YR 2/2			
	36	SiL	20	10YR 3/2	5% D	5% 10YR 4/1	
	50	SiCL	30	10YR 3/2	5% D	5% 10YR 4/1	
	79	SiCL	35	10YR 3/2	10% D	8% 10YR 4/1	
	99	SiC	42	10YR 3/1	30% P	30% 7.5YR 6/1	
	104	SiC	42	5Y 6/1	45% P		

Site: SDI 3B depression outer   **Described:** M. Goldman, K. Rankin 7/13/2015
Landcover: Forest   **Water Table:** 72 cm
Drainage Class: VPD   **Texture Group:** Fine

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
Oe	4			2.5YR 2.5/1			
A1	27	SiL	12	10YR 2/2			
A2	35	SiL	12	10YR 2/2		2% 10YR 4/1	
	62	SiCL	29	2.5Y 5/1	3% D		3% small rocks and gravels
	82	SiCL	32	2.5Y 5/1	8% P		3% small rocks and gravels
	98	CL	38	5Y 6/1	8% P		5% small rocks and gravels
	112	S	3	2.5Y 7/1			

Site: SDI 3C slope **Described:** M. Goldman, K. Rankin 7/13/2015
Landcover: Forest **Water Table:** 96 cm
Drainage Class: VPD **Texture Group:** Fine

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
Oe	8			5YR 2.5/2			
A	30	SiL	12	10YR 2/2			
	50	SiL	25	2.5Y 4/1			
	67	SiCL	33	2.5Y 4/1	5% P		
	81	SiCL	33	2.5Y 5/1	20% P	small rocks and gravels increasing from 2% - 10% moving down	
	97	CL	37	2.5Y 6/1			
	103	SL	18	2.5Y 6/1		20% small rocks and gravels	

Site: SDI 3D rim **Described:** M. Goldman, K. Rankin 7/13/2015
Landcover: Forest **Water Table:** 96 cm
Drainage Class: VPD **Texture Group:** Fine

Comments:

Horizon	Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
A1	8	L	12	2.5Y 2.5/2			
A2	33	L	12	10YR 2/2			
	46	SL	7	10YR 3/2			
	52	LS	3	2.5Y 6/2			
	62	SiCL	33	5Y 6/1	10% P		
	81	CL	29	5Y 6/1	15% D, 5% P		
	90	CL	33	5Y 6/1			
Cg	106	too gravelly to texture, but still a bit of clay		5Y 6/1			very gravelly, small rounded rocks

Site: TJR 6A depression inner   **Described:** M. Goldman, C. Seitz 9/18/15
Landcover: Forest   **Water Table:** 64 cm
Drainage Class: VPD   **Texture Group:** Fine

Comments: used moss line to define edge of depression (no groundcover in center)

Horizon	Depth	Texture	Clay%	Color	Conc.	Depl.	Comments
	10			7.5YR 2.5/2			
	25	SiL (mucky?)	16	10YR 2/1			
	41	SiL	15	10YR 3/2			mica?
	63	SiL	26	10YR 3/2	15% D		mica?
	85	SiCL	34	10YR 3/2	25% P	2% 10YR 5/1	mica?
	93	SiCL	32	10YR 3/2	25% P	10% 10YR 5/1	
	110	SiCL	37	2.5Y 6/1	25% P		

Site: TJR 6B depression outer   **Described:** M. Goldman, C. Seitz 9/18/15
Landcover: Forest   **Water Table:** not reached
Drainage Class: VPD   **Texture Group:** Fine

Comments:

Horizon	Depth	Texture	Clay%	Color	Conc.	Depl.	Comments
Oe	6						
A	11			7.5YR 2.5/2			
	32	L (not quite mucky)	14	10YR 2/1			>20% unncoated
	43	L (not quite mucky)	17	10YR 2/1		5% 10YR 5/1	
	57	SCL (close to CL)	30	10YR 2/2	5% D	10% 10YR 5/1	organics
	75	SCL (close to CL)	33	10YR 5/1	15% P		organics
	100	SL (toward bottom of horizon)	19		5% P		

Site: TJR 6C slope **Described:** Maggie Goldman, Chris Seitz 9/18/15
Landcover: Forest **Water Table:** not reached
Drainage Class: MWD **Texture Group:** Coarse

Comments:

Horizon	Depth	Texture	Clay%	Color	Conc.	Depl.	Comments
	16	L	8	10YR 2/1			50% uncoated
	30	L	13	10YR 2/2			25% uncoated
	43	SL	8	10YR 4/2			Transition
	57	LS	4	10YR 5/2			
	79	SCL	23	10YR 3/1	5% D	10% 10YR 4/1	organics
	89	SL	13	10YR 5/2	10% P		organics
	102	SL	17	2.5Y 5/2	5% D		
	107	SCL	33	5Y 5/2	5% D		

Site: TJR 6D rim **Described:** M. Goldman, C. Seitz 9/18/15
Landcover: Forest **Water Table:** not reached
Drainage Class: MWD **Texture Group:** Coarse

Comments:

Horizon	Depth	Texture	Clay%	Color	Conc.	Depl.	Comments
Oe	10			5YR 2.5/2			
A	22	SL	11	10YR 2/2			50% uncoated
	29	LS	4	10YR 4/2	10% D, 5% P		
	55	SL	3	10YR 5/2	10% D		
	87	SL	13	2.5Y 6/1	30% P		
	105	SL	10	5Y 6/1	25% P including pockets of 7.5YR 5/8		

Site: TJR 5A depression inner   **Described:** M. Goldman, C. Seitz 9/20/15
Landcover: Forest   **Water Table:** 23
Drainage Class: VPD   **Texture Group:** Fine

Comments:

Horizon	Depth	Texture	Clay%	Color	Conc.	Depl.
	9			5YR 2.5/2		
	14			10YR 2/1		
	25	SiL	11	10YR 2/1		
	40	SiL	8	10YR 2/1		
	59	SiL	21	10YR 2/1		
	85	SiCL	33	10YR 2/1	10% D to 20% P beginning at 72 cm	
	90	SiC	42	10YR 2/1, pockets of 10YR 4/3	10% P	
	112	SiCL	28	7.5YR 3/2	5% D	
	117			2.5Y 3/2	5% D	

Site: TJR 5B depression outer   **Described:** M. Goldman, C. Seitz 9/20/15
Landcover: Forest   **Water Table:** not recorded
Drainage Class: PD   **Texture Group:** Fine

Comments:

Horizon	Depth	Texture	Clay%	Color	Conc.	Depl.	Comments
	10			5YR 2.5/2			Top 2 horizons >20% sand, then sand disappears
	31	SiL	14	10YR 2/1		1% 10YR 4/2	10% uncoated
	50	SiL	10	10YR 2/1	5% D	1% 10YR 4/2	
	63	SiL	18	10YR 2/1	5% D (1% P)	1% 10YR 4/1	
	75	SiCL	30	10YR 2/2	30% P	30% 2.5Y 5/1	pockets of organics
	93	SiC	41	5Y 5/1	15% P		
	107	SiC	47	2.5Y 4/1	15% P		

Site: TJR 5C slope **Described:** M. Goldman, C. Seitz 9/20/15
Landcover: Forest **Water Table:** 119 cm
Drainage Class: MWD **Texture Group:** Coarse

Comments:

Horizon	Depth	Texture	Clay%	Color	Conc.	Depl.	Comments
	8			5YR 2.5/1			
AE	38	SL	8	10YR 2/1			25% uncoated
E	52	LS	5	10YR 4/2			
EB	63	SL	2	2.5Y 6/2			
Btg1	81	SCL	28	2.5Y 5/1	20% P		
Btg2	90	C	41	5Y 6/1	10% P		
Cg	100	S	1	2.5Y 7/1			

Site: TJR 5D rim **Described:** Maggie Goldman, Chris Seitz 9/20/15
Landcover: Forest **Water Table:** 146 cm
Drainage Class: MWD **Texture Group:** Coarse

Comments:

Horizon	Depth	Texture	Clay%	Color	Conc.	Depl.	Comments
	9			5YR 2.5/1			
	15	L	9	7.5YR 2.5/1			10% uncoated
	20	L	9	10YR 3/2			10% uncoated
	31	SiL	19	10YR 3/4			
	50	L	25	10YR 3/6	3% P		
	65	SCL	22	2.5Y 4/3	15% D (2% P)		
	86	LS	4	2.5Y 5/2	25% P		
	96	S	1	2.5Y 7/1	5% D		
	104	S	2	2.5Y 6/4	20% D (5% P)		

Site: CLN 13A depression inner **Described:** M. Goldman, C. Seitz 9/3/15
Landcover: Forest **Water Table:** 6 cm
Drainage Class: VPD **Texture Group:** Fine

Comments:

Horizon	Depth	Texture	Clay%	Color	Conc.	Depl.	Comments
Oe	7			7.5YR 2.5/1			
A1	20	SiL	8	10YR 2/2			
A2	42	SiCL	29	10YR 2/2			<15% S
Bg1	53	SiCL	31	2.5Y 4/2	5% D along roots		<15% S
Bg2	70	L	26	2.5Y 4/2	5% D along roots		

Site: CLN 13B depression outer **Described:** M. Goldman, C. Seitz 9/3/15
Landcover: Forest **Water Table:** 22 cm
Drainage Class: VPD **Texture Group:** Fine

Comments:

Horizon	Depth	Texture	Clay%	Color	Conc.	Depl.	Comments
Oe	8			10YR 2/2			
A1	16			10YR 2/2			
A2	28	SiL	8	10YR 2/1		3% 2.5Y 6/1	
AB	45	SiCL	28	10YR 2/1			
Bg1	85	SiCL	30	10YR 4/2	10% D		
Bg2	102	SiCL	32	10YR 4/1	10% D		

Site: CLN 13C slope **Described:** M. Goldman, C. Seitz 9/3/15
Landcover: Forest **Water Table:** not reached
Drainage Class: MWD **Texture Group:** Coarse

Comments:

Horizon	Depth	Texture	Clay%	Color	Conc.	Depl.	Comments
Oe	11						
AE	35	L (close to SL)	12	10YR 2/2			uncoated mineral grains
	46	SL	17	10YR 2/2			
B/A	60	SCL	21	50% 10YR 2/2 and 50% 10YR 5/3			
Bg	82	SL	11	2.5Y 6/2			
BCg	96	LS	5	2.5Y 6/2			
Cg	106	S	3	2.5Y 6/2			

Site: CLN 13D rim **Described:** M. Goldman, C. Seitz 9/3/15
Landcover: Forest **Water Table:** not reached
Drainage Class: WD **Texture Group:** Coarse

Comments:

Horizon	Depth	Texture	Clay%	Color	Conc.	Depl.	Comments
Oe	7			5YR 2.5/2			
AE	11	SL	8	10YR 2/2			uncoated mineral grains
Bw1	25	SL	10	10YR 4/4			
Bw2	64	LS	6	10YR 5/4			
Bw3	75	LS	5	10YR 4/6			
Bw4	92	LS	4	10YR 5/6			
Bw5	100	SL	4	10YR 5/6	7.5YR 4/6 nodules		

Site: CLN 9A depression inner **Described:** M. Goldman, C. Seitz 9/3/15
Landcover: Forest **Water Table:** not reached
Drainage Class: VPD **Texture Group:** Fine

Comments:

Horizon	Depth	Texture	Clay%	Color	Conc.	Depl.	Comments
Oe	8			10YR 2/2			
A	17	SiL	20	10YR 3/2		1% 2.5Y 6/1	<15% sand in all horizons
AB	42	SiCL	36	10YR 3/2	10% P	20% 2.5Y 6/1	
Bg	66	SiCL	42	2.5Y 5/1	10% P		
Bg	94	SiCL	46	5Y 6/1	40% P		

Site: CLN 9B depression outer **Described:** M. Goldman, C. Seitz 9/3/15
Landcover: Forest **Water Table:** not recorded
Drainage Class: VPD **Texture Group:** Coarse

Comments:

Horizon	Depth	Texture	Clay%	Color	Conc.	Depl.	Comments
Oe	6			7.5YR 2.5/2			
AE	13	SiL	16	7.5YR 2.5/1			uncoated mineral grains
	39	SiL	24	7.5YR 2.5/1		5% 2.5Y 4/1	
Btg1	57	SiCL	36	10YR 4/1			
Btg2	84	SiC	41	10YR 4/1	20% P		
BCg	100	SiC	45	2.5Y 5/1	20% P		

Site: CLN 9C slope   **Described:** M. Goldman, C. Seitz 9/3/15
Landcover: Forest   **Water Table:** not reached
Drainage Class: SWPD   **Texture Group:** Coarse

Comments:

Horizon	Depth	Texture	Clay%	Color	Conc.	Depl.	Comments
Oe	2			7.5YR 2.5/2			
AE	15	SL (L?)	12	10YR 2/2			hi organic; uncoated mineral grains
E	31	SL	10	10YR 3/3			uncoated mineral grains
	48	SL	12	10YR 3/2		1% 2.5Y 5/2	
	62	SL	14	10YR 3/2		30% 2.5Y 5/2	
Cg1	78	LS	6	2.5Y 6/1			
Cg2	100	S	4	2.5Y 7/1			

Site: CLN 9D rim   **Described:** M. Goldman, C. Seitz 9/3/15
Landcover: Forest   **Water Table:** not reached
Drainage Class: WD   **Texture Group:** Coarse

Comments:

Horizon	Depth	Texture	Clay%	Color	Conc.	Depl.	Comments
Oe	6			7.5YR 2.5/2			
AE	15	LS	9	10YR 2/2			uncoated mineral grains
Bw1	71	LS	4	2.5Y 5/4			
Bw2	81	LS	6	2.5Y 5/6			
Bw3	97	LS	6	2.5Y 5/4	5% D		
BC	114	LS	5	2.5Y 6/3	15% D		
Cg	118			2.5Y 6/1	20% P		

Site: CLN 14A depression inner   **Described:** M. Goldman, C. Seitz 9/11/15
Landcover: Forest   **Water Table:** 13 cm
Drainage Class: VPD   **Texture Group:** Fine

Comments:

Horizon	Depth	Texture	Clay%	Color	Conc.	Depl.	Comments
Oe	8						from 0-35 goes from fibrous to mucky; black at 16cm
O	22						Compression when auguring so depths very rough
O	35						marsh grasses
A	49	SiL	10	10YR 2/1			
BA	75	SiC	43	10YR 3/2			
B	110	SiC	47	10YR 4/2			

Site: CLN 14B depression outer   **Described:** M. Goldman, C. Seitz 9/11/15
Landcover: Forest   **Water Table:** 95 cm
Drainage Class: VPD   **Texture Group:** Fine

Comments:

Horizon	Depth	Texture	Clay%	Color	Conc.	Depl.	Comments
Oe	10			7.5YR 2.5/2			
A	18	SiL	13	10YR 2/1			35% sand
AE	40	L	9	10YR 2/1			45% sand
Bt	58	CL	30	10YR 3/2		5% 10YR 4/2	
Btg	70	SCL	33	10YR 4/2			
BCg	82	SL	19	10YR 5/2			
Cg	101	LS	6	10YR 6/2			

Site: CLN 14C slope
Landcover: Forest
Drainage Class: WD

Described: M. Goldman, C. Seitz 9/11/15
Water Table: saturated at 156 cm
Texture Group: Coarse

Comments:

Horizon	Depth	Texture	Clay%	Color	Conc.	Depl.	Comments
Oe	12			5YR 2.5/2			spodic properties
AE	35	LS	5	10YR 2/1			uncoated mineral grains
	57	S	4	10YR 2/2			dark
Bhs	75	LS	4	7.5YR 3/2			reddish brown and dark brown-black
	91	LS	4	5YR 3/3			coffee red with pockets of black
	110	S	4	7.5YR 5/6			lighter w/ pockets of red and black

Site: CLN 14D rim
Landcover: Forest
Drainage Class: WD

Described: M. Goldman, C. Seitz 9/11/15
Water Table: saturated at 156 cm
Texture Group: Coarse

Comments:

Horizon	Depth	Texture	Clay%	Color	Conc.	Depl.	Comments
Oe	3			5YR 2.5/2			
A	8	SL	11	10YR 3/3			
	15	SL	13	10YR 4/3			
	29	SL	15	10YR 5/6			
	54	SL	17	10YR 5/6			
	63	L	17	10YR 4/6			transition
	84	L	26	7.5YR 5/6			
	111	LS	5	10YR 4/6			

Site: JLH 4A depression inner   **Described:** M. Goldman, C. Seitz 4/16/15
Landcover: Crop   **Water Table:** not recorded
Drainage Class: PD   **Texture Group:** Fine

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
16	SiL	12	2.5Y 4/2			
39	SiL	17	2.5Y 5/1	10% D		
52	SiL	26	2.5Y 6/1	5% D		
78	SiCL	30	2.5Y 6/1	22% D		
91	SCL	34	5Y 6/1	<5% D		crumbly coarse sand, 5% coarse frags, chert
95	SCL	34	5Y 7/1	15% D		sticky, 10% coarse frags, chert, quartz

Site: JLH 4B depression outer   **Described:** M. Goldman, C. Seitz 4/16/15
Landcover: Crop   **Water Table:** 90 cm
Drainage Class: PD   **Texture Group:** Fine

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
26	L	10	2.5Y 4/2	10% F		
39	SL	20	2.5Y 5/2			
70	SL	11	2.5Y 6/1	15% D		
87	SCL	26	2.5Y 5/1	30% D		5% coarse frags, chert
101	SCL	29	2.5Y 6/1	5% D		7% coarse frags, chert

Site: JLH 4C slope   **Described:** M. Goldman, C. Seitz 4/16/15
Landcover: Crop   **Water Table:** not recorded
Drainage Class: WD   **Texture Group:** Coarse

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
25	SL	9	10YR 4/3			
35	SL	12	10YR 4/4			
49	SL	18	10YR 4/4			
59	SCL	21	10YR 4/4			
70	SL	17	10YR 4/4			
87	LS	6	10YR 4/6			
102	LS	5	10YR 4/6			

Site: JLH 4D rim   **Described:** M. Goldman, C. Seitz 4/16/15
Landcover: Crop   **Water Table:** not recorded
Drainage Class: WD   **Texture Group:** Coarse

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
29	SL	7				
40	SL	11				
55	SL	15				
87	LS	10				
101	LS	7				

Site: JLH 2A depression inner   **Described:** M. Goldman, C. Seitz 4/16/15
Landcover: Crop   **Water Table:** 82 cm
Drainage Class: PD   **Texture Group:** Coarse

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
28	SiL	15	2.5Y 4/3	5% D along root channels		
57	SiL	12	2.5Y 6/1	2% D		
74	SiL	20	2.5Y 5/1	30% D		
98	L	20	2.5Y6/1	20% D		

Site: JLH 2B depression outer   **Described:** M. Goldman, C. Seitz 4/16/15
Landcover: Crop   **Water Table:** 71 cm
Drainage Class: PD   **Texture Group:** Coarse

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
34	SiL	7	2.5Y 4/2	5% D		
66	L	19	2.5Y 6/1	15% P		
90	SL	18	2.5Y 6/1	20% P		
98	SL	10	2.5Y 6/1	10% P		

Site: JLH 2C slope   **Described:** M. Goldman, C. Seitz 4/16/15
Landcover: Crop   **Water Table:** not recorded
Drainage Class: PD   **Texture Group:** Coarse

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
32	SL	7	2.5Y 4/2			
52	LS	6	2.5Y 6/2			
86	LS	4	2.5Y 6/2	10% P, black in center of firm nodules		
100	S	2	2.5Y 7/1			

Site: JLH 2D rim   **Described:** M. Goldman, C. Seitz 4/16/15
Landcover: Crop   **Water Table:** not recorded
Drainage Class: WD   **Texture Group:** Coarse

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
30	SL	8	2.5Y 4/2			
52	LS	7	2.5Y 5/6			
77	LS	5	2.5Y 5/4			
96			2.5Y 6/4	10% D		

Site: JLH 10A depression inner   **Described:** M. Goldman, C. Seitz 4/16/15
Landcover: Crop   **Water Table:** ponded
Drainage Class: PD   **Texture Group:** Coarse

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
36	SiL	8	2.5Y 5/2	10% D		
54	SL	8	2.5Y 4/2		2.5Y 5/2, 5% D	
74	SL	18	2.5Y 6/1	10% D		

Site: JLH 10B depression outer   **Described:** M. Goldman, C. Seitz 4/16/15
Landcover: Crop   **Water Table:** 21 cm
Drainage Class: PD   **Texture Group:** Coarse

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
54	L	11	2.5Y 4/2	5%		
72	SL	9	2.5Y 6/1	10% D		
88	SCL	22	2.5Y 6/1	30% D		
98	SL	19	2.5Y 6/1	30% D		

Site: JLH 10C slope   **Described:** M. Goldman, C. Seitz 4/16/15
Landcover: Crop   **Water Table:** 92 cm
Drainage Class: MWD   **Texture Group:** Coarse

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
39	SL	8	2.5Y 4/2			
54	SL	10	2.5Y 6/2	3% F		
70	SL	18	2.5Y 6/4	10% D		
82	SCL	25	2.5Y 7/1	30% D		
100	SCL	23	2.5Y 7/1	30% D		

Site: JLH 10D rim   **Described:** M. Goldman, C. Seitz 4/16/15
Landcover: Crop   **Water Table:** not recorded
Drainage Class: WD   **Texture Group:** Coarse

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
26	SL	10	2.5Y 4/2			
58	SL	14	10YR 4/4			
101	SL	8	10YR 5/6			

Site: JLW 1A depression inner   **Described:** M. Goldman, C. Seitz 4/19/15
Landcover: Crop   **Water Table:** 75 cm
Drainage Class: VPD   **Texture Group:** Fine

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
29	SL	13	10YR 2/1			
48	L	18	2.5Y 6/1	15% D		
64	CL	34	2.5Y 6/1	10% D		
82	CL	35	2.5Y 6/1	5% D		
90	LS	7	2.5Y 7/1	5% D (2% D)		
101	LS	9	2.5Y 7/1	25% D, 10% P		

Site: JLW 1B depression outer   **Described:** M. Goldman, C. Seitz 4/19/15
Landcover: Crop   **Water Table:** 98 cm
Drainage Class: VPD   **Texture Group:** Fine

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
30			10YR 2/1			
40	L	18	2.5Y 4/1	2% P		
54	CL*	31	5Y 5/1	5% D, 10% P	5Y 6/1, 20%	
67	CL*	33	5Y 6/1	3% D, 15% P		
91	SL	10	2.5Y 7/1	10% D, 2% P		
101	SL	13	2.5Y 6/1	10% P		

Site: JLW 1C slope **Described:** M. Goldman, C. Seitz 4/19/15
Landcover: Crop **Water Table:** 97 cm
Drainage Class: MWD **Texture Group:** Fine

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
30	SL	8	10YR 3/1			
40	SL	10	2.5Y 4/1			
55	LS	7	10YR 5/6 or 7.5YR 4/6			
69	LS	6	10YR 5/6 or 7.5YR 4/6		25%	
88	fine SCL	35	5Y 7/1	15% P		
100	fine SCL	33		5% P		

Site: JLW 1D rim **Described:** M. Goldman, C. Seitz 4/19/15
Landcover: Crop **Water Table:** not recorded
Drainage Class: SWPD **Texture Group:** Coarse

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
21	SL	12	10YR 3/2			
44	SL	12	2.5Y 5/4			
51	SL	14	2.5Y 5/4	15% D	35% 2.5Y 7/1	
84	SL	10	2.5Y 7/1	15% D		
98	LS	5	2.5Y 5/4	30% D	30% 2.5Y 7/1	3% coarse frags
110	S	3	2.5Y 7/1			

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Site: JLW 3A depression inner   **Described:** M. Goldman, C. Seitz 4/19/15
Landcover: Crop   **Water Table:** 17 cm
Drainage Class: VPD   **Texture Group:** Fine

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
9	Mucky L	14	10YR 2/1			
30	SiL	13	10YR 2/1			
50	SiL	25	2.5Y 5/1	5% D, 10% P	5% 10YR 6/1	
70	SiL	26	2.5Y 6/2	5% D, 10% P		
82	SiL	24	2.5Y 5/2	10% P		

Site: JLW 3B depression outer   **Described:** M. Goldman, C. Seitz 4/19/15
Landcover: Crop   **Water Table:** 60 cm
Drainage Class: VPD   **Texture Group:** Fine

Comments: Same as JLW 3A. Muck to 6 cm. bottom of A at 30 cm. Clay jump at 30 cm. Concentrations and depleted matrix at 44 cm. SiL textures.

Site: JLW 3C slope   **Described:** M. Goldman, C. Seitz 4/19/15
Landcover: Crop   **Water Table:** 92 cm
Drainage Class: VPD   **Texture Group:** Coarse

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
30	SL	13	10YR 2/1			
52	SL	18	10YR 4/1			
65	LS	8	10YR 5/1			
90	SCL	23	2.5Y 7/1	30% P		2% coarse frags, chert
100	LS	13	2.5Y 6/1	10% D		

Site: JLW 3D rim   **Described:** M. Goldman, C. Seitz 4/19/15
Landcover: Crop   **Water Table:** 92 cm
Drainage Class: VPD   **Texture Group:** Coarse

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
30	SL	13	10YR 3/2			
60	LS	9	10YR 6/1			
105	SL	4	2.5Y 6/2	10% P to 71, 20% D to87	10% at 87	

Site: JLW 2A depression inner   **Described:** M. Goldman, C. Seitz 4/21/15
Landcover: Crop   **Water Table:** 57 cm
Drainage Class: VPD   **Texture Group:** Coarse

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
6	L	11	10YR 2/2			
30	L	15	10YR 3/2			
41	LS	4	2.5Y 5/2			
62	SL	17	2.5Y 4/1			
74	SL	14	2.5Y 6/1	10% D		
83	SL	10	2.5Y 6/2	30% D		
100	SL	12	2.5Y 7/1	5% D		

Site: JLW 2B depression outer   **Described:** M. Goldman, C. Seitz 4/21/15
Landcover: Crop   **Water Table:** 89 cm
Drainage Class: VPD   **Texture Group:** Coarse

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
32	L	15	10YR 3/2	10% D (along root channels)		
40	SL	16	2.5Y 5/2	5% D		
50	SL	13	2.5Y 6/2	5% D		
64	SL	18	2.5Y 5/1			
88	SL	16	2.5Y 6/1	15% D		
102	SCL	25	2.5Y 6/1			

Site: JLW 2C slope **Described:** M. Goldman, C. Seitz 4/21/15
Landcover: Crop **Water Table:** 89 cm
Drainage Class: SWPD **Texture Group:** Fine

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
24	SL	14	10YR 3/2			
38	SL	18	10YR 5/3			
57	SL	18	2.5YR 6/2			
68	SL	19	2.5YR 6/1	5% D		
98	SL	19	2.5YR 6/1	25% D		
108	SCL	28	5Y 6/1			

Site: JLW 2D rim **Described:** M. Goldman, C. Seitz 4/21/15
Landcover: Crop **Water Table:** 96 cm
Drainage Class: MWD **Texture Group:** Coarse

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
25	L	12	10YR 4/3			
43	SL	18	10YR 5/3			
69	SCL	24	10YR 5/3			
99	S	2	2.5Y 7/1	25% D		
108	LS	4	2.5Y 7/1	20% P	15% 10YR 5/4	

Site: BJC 4A depression inner   **Described:** M. Goldman, C. Seitz 5/5/15
Landcover: Crop   **Water Table:** 92 cm
Drainage Class: VPD   **Texture Group:** Fine

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
21	SiL	15	10YR 3/1			
30	SiL	15	10YR 3/1		2% 10YR 4/1	
54	SiCL	37	2.5Y 5/2	30% P		
73	SiCL	37	2.5Y 6/1	15% P	5% 2.5Y 7/1	
100	SiCL	39	2.5Y 6/1	40% P		

Site: BJC 4B depression outer   **Described:** M. Goldman, C. Seitz 5/5/15
Landcover: Crop   **Water Table:** 100 cm
Drainage Class: VPD   **Texture Group:** Fine

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
36	L	15	10YR 2/1			
59	SL	15	2.5Y 4/1		5% 2.5Y 6/2	
70	SL	18	2.5Y 5/1	10% D, 2% P	5% 2.5Y 6/2	
97	CL	38	2.5Y 7/1	30% P	15% 2.5Y 4/1	
109	SCL	34	2.5Y 7/1		15% 2.5Y 4/1	

Site: BJC 4C slope   **Described:** M. Goldman, C. Seitz 5/5/15
Landcover: Crop   **Water Table:** 71 cm
Drainage Class: MWD   **Texture Group:** Coarse

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
25	SL	10	10YR 3/2			
65	LS	5	2.5Y 6/4	20-40% D increasing downward		
81	LS	4	2.5Y 6/4			
96	LS	4	2.5Y 6/4			
100	S	3	2.5Y 7/1			

Site: BJC 4D rim   **Described:** M. Goldman, C. Seitz 5/5/15
Landcover: Crop   **Water Table:** 90 cm
Drainage Class: MWD   **Texture Group:** Coarse

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
21	SL	10	10YR 4/3			
62	SL	14	2.5Y 5/4	15% D, 2% P	10% 2.5Y 5/3	
90	LS	4	2.5Y 6/4	15% D		
100	S	3	2.5Y 7/2	10% P		

Site: BJC 3A depression inner   **Described:** M. Goldman, C. Seitz 5/5/15
Landcover: Crop   **Water Table:** not recorded
Drainage Class: VPD   **Texture Group:** Coarse

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
30	L (SL)	12	10YR 3/1			
72	L (SL)	18	2.5Y 5/1	10% D	5% 2.5YR 6/1	
83	SCL	25	2.5Y 6/1	30% P		
106	LS (S)	4	2.5Y 7/1	15% P		

Site: BJC 3B depression outer   **Described:** M. Goldman, C. Seitz 5/5/15
Landcover: Crop   **Water Table:** not recorded
Drainage Class: VPD   **Texture Group:** Fine

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
30	SiL	13	10YR 3/1			
60	SiL	16	10YR 3/2	5% D		
89	SiL	22	5YR 6/1	10% P		
100	SiCL	34	5YR 6/1	35% P		

Site: BJC 3C slope   **Described:** M. Goldman, C. Seitz 5/5/15
Landcover: Crop   **Water Table:** not recorded
Drainage Class: PD   **Texture Group:** Fine

Comments: sand over 20%

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
34	SiL	14	10YR 3/2		~1% 2.5Y 6/2 starting at 30 cm	
63	SiL	18	10YR 4/1			
74	SiL	25	10YR 4/1	5% D	30% 2.5Y 6/2	3% BD chert
85	SiCL	31	10YR 4/1	30% P	35% 5Y 6/1	7% BD chert
101	SiL	26	5Y 6/1	30% P		4% BD chert

Site: BJC 3D rim   **Described:** M. Goldman, C. Seitz 5/5/15
Landcover: Crop   **Water Table:** not recorded
Drainage Class: VPD   **Texture Group:** Fine

Comments: sand over 20%

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
34	SiL	15	10YR 3/2			
57	SiL	16	2.5Y 4/1		35% 2.5Y 5/1	
81	SiL	18	2.5Y 5/1	5% D		
94	SiL	20	2.5Y 5/1	15% D	40% 5Y 6/1	
101	SiL	26	5Y 6/1	25% P		

Site: BJC 5A depression inner   **Described:** M. Goldman, C. Seitz 5/6/15
Landcover: Crop   **Water Table:** 107 cm
Drainage Class: PD   **Texture Group:** Fine

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
20	L	15	10YR 4/2	15% D along roots		
47	SiL	23	10YR 4/2	5% D		
65	SiCL	38	2.5Y 4/1	15% P		
97	SiC	42	2.5Y 4/1	2.5Y 4/1	5Y 7/1	
107	SiC	42	2.5Y 5/1	2.5Y 5/1	5Y 7/1	

Site: BJC 5B depression outer   **Described:** M. Goldman, C. Seitz 5/6/15
Landcover: Crop   **Water Table:** 88 cm
Drainage Class: PD   **Texture Group:** Fine

Comments: borderline VPD

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
14	L	12	10YR 3/2			
40	SL	9	10YR 4/2	15% D along roots		
53	L	15	2.5Y 5/2			
84	SL	20	5Y 6/1	25% P		
100	SCL	26	5Y 6/1	15% P		
110	SCL	34	5Y 6/1	20% P		2% BD chert

Site: BJC 5C slope   **Described:** M. Goldman, C. Seitz 5/6/15
Landcover: Crop   **Water Table:** 95 cm
Drainage Class: WD   **Texture Group:** Coarse

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
13	SL	9	10YR 4/3			
67	SL	10	10YR 5/4			
88	LS	5	10YR 5/6	15% D		
109	S	3	10YR 5/6	15% D		

Site: BJC 5D rim   **Described:** M. Goldman, C. Seitz 5/6/15
Landcover: Crop   **Water Table:** not recorded
Drainage Class: WD   **Texture Group:** Coarse

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
13	SL	9	10YR 4/3			
30	SL	8	10YR 4/4			
70	LS	10	10YR 5/6			
85	LS	4	10YR 5/6			5% BD chert
112	LS	4	10YR 5/6	10% P Mn		6% BD chert

Site: CSH 14A depression inner   **Described:** M. Goldman, K. Rankin, C. Seitz 5/14/15
Landcover: Crop   **Water Table:** not recorded
Drainage Class: PD   **Texture Group:** Fine

Comments: borderline VPD

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
45	SiL	16	10YR 4/3	15% D along roots		
61	SiL	25	2.5Y 5/2	10% D along roots		
78	SiCL	32	2.5Y 5/2	10% D along roots, 5% P		
95	SiCL	28	2.5Y 6/1			2% chert
102	SCL	28	2.5Y 6/1	15% D		20% coarse frags
107	gravel		2.5Y 6/1, 10YR 5/6			

Site: CSH 14B depression outer   **Described:** M. Goldman, K. Rankin, C. Seitz 5/14/15
Landcover: Crop   **Water Table:** not recorded
Drainage Class: PD   **Texture Group:** Fine

Comments: borderline VPD

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
23	SiL	13	10YR 4/2	10% D along root channels		
53	SiL	16	2.5Y 6/2	25% P		
88	CL	28	2.5Y 6/1	20% P		
96	S	3	2.5Y 7/1	10% P at very top of horizon		

Site: CSH 14C slope   **Described:** M. Goldman, K. Rankin, C. Seitz 5/14/15
Landcover: Crop   **Water Table:** not recorded
Drainage Class: MWD   **Texture Group:** Coarse

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
42	SiL	10	10YR 4/2			
72	CL	30	2.5Y 5/2	20% P		
93	LS	6	40% 2.5Y 6/4			
102	LS	5	5Y 7/1 and 40% 2.5Y 7/4	20% P		

Site: CSH 14D rim   **Described:** M. Goldman, K. Rankin, C. Seitz 5/14/15
Landcover: Crop   **Water Table:** not recorded
Drainage Class: MWD   **Texture Group:** Coarse

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
49	L	12	10YR 4/2			
72	CL	28	2.5Y 5/3	25% P Fe and Mn		
85	SL	10	2.5Y 5/2	20% P		
100	LS	5	50% 2.5Y 7/1 and 50% 2.5Y 6/4			

Site: CSH 12A depression inner   **Described:** M. Goldman, K. Rankin, C. Seitz 5/14/15
Landcover: Crop   **Water Table:** 94 cm
Drainage Class: PD   **Texture Group:** Coarse

Comments: borderline VPD

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
30	SiL	16	10YR 4/2	5% D		
54	SL	12	2.5Y 5/2	8% P Fe and Mn		
69	SL	12	2.5Y 5/2	12% P Fe and Mn		
82	LS	5	2.5Y 6/1	5% P Fe around Mn		
103	LS	5	2.5Y 6/1	40% brown, red, black		Many colors: orange, black, grey

Site: CSH 12B depression outer   **Described:** M. Goldman, K. Rankin, C. Seitz 5/14/15
Landcover: Crop   **Water Table:** 92 cm
Drainage Class: PD   **Texture Group:** Coarse

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
30	SiL	9	10YR 4/3			
59	L	12	2.5Y 5/2	5%		
75	SL	16	2.5Y 6/1	15% Mn nodules and Fe		
90	LS	5	2.5Y 7/1	15% P; coffee brown masses Fe and Mn		
100	LS	5	10YR 5/4, 2.5Y 6/2			

Site: CSH 12C slope **Described:** M. Goldman, K. Rankin, C. Seitz 5/14/15
Landcover: Crop **Water Table:** not recorded
Drainage Class: MWD **Texture Group:** Coarse

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
30	SL	9	10YR 4/3			
46	SL	10	2.5Y 5/4	5% D		
62	SL	12	2.5Y 5/4			
80	L	14	2.5Y 5/6	15% Mn, 10% D Fe		
90	CL	29	2.5Y 5/4	15% Mn, 10% D Fe		
102	CL	37	2.5Y 7/1	20% P Fe		

Site: CSH 12D rim **Described:** M. Goldman, K. Rankin, C. Seitz 5/14/15
Landcover: Crop **Water Table:** not recorded
Drainage Class: WD **Texture Group:** Coarse

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
30	LS	6	10YR 4/3			
55	LS	6	10YR 5/6			
100	LS	6	10YR 5/6	10% D 7.5YR 5/6, 5% Mn		

Site: CSH 13A depression inner   **Described:** M. Goldman, K. Rankin, C. Seitz 5/14/15
Landcover: Crop   **Water Table:** 92 cm
Drainage Class: MWD   **Texture Group:** Coarse

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
30	SL	7	10YR 4/3			
53	SL	9	2.5Y 5/4	5% P		
71	L	12	2.5Y 5/3	5% P		
87	L	14	2.5Y 4/1			
101	L	23	2.5Y 6/1	10% D/P		

Site: CSH 13B depression outer   **Described:** M. Goldman, K. Rankin, C. Seitz 5/14/15
Landcover: Crop   **Water Table:** not recorded
Drainage Class: MWD   **Texture Group:** Coarse

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
43	SL	7	10YR 4/3			
52	L	21	2.5Y 5/4			
65	L	24	2.5Y 5/4	10% P		
72	SL	19	2.5Y 6/2	30% P		
82	SL	10	10YR 5/6			
93	SCL	21	2.5Y 7/1	40% 10YR 5/6		20% gravels

Site: CSH 13C slope   **Described:** M. Goldman, K. Rankin, C. Seitz 5/14/15
Landcover: Crop   **Water Table:** not recorded
Drainage Class: MWD   **Texture Group:** Coarse

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
30	SL	7	10YR 4/3			
52	L	23	10YR 5/6	5% D	10% 10YR 5/2-5/3	
80	LS	6	10YR 5/6	10% D		
89	LS	6	2.5Y 5/3	40% 10YR 5/6		
100	LS	6	2.5Y6/1	40% 10YR 5/6, 5% P cemented Fe conc.		

Site: CSH 13D rim   **Described:** M. Goldman, K. Rankin, C. Seitz 5/14/15
Landcover: Crop   **Water Table:** not recorded
Drainage Class: WD   **Texture Group:** Fine

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
30	SiL	9	10YR 4/3			
70	SiL	25	10YR 4/6			
87	L	18	10YR 4/6			
109	LS	6	10YR 5/6			

Site: MAS 15A depression inner   **Described:** M. Goldman, K. Rankin 6/1/15
Landcover: Crop   **Water Table:** not recorded
Drainage Class: WD   **Texture Group:** Fine

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
19	SiL	15	10YR 4/3	5% D along roots		
36	SiL	17	10YR 4/3	5% D		
47	SiL	23	2.5Y 5/4	5% D		
67	SiCL	33	10YR 6/6			
100	SiCL	37	10YR 5/6	20% P		

Site: MAS 15B depression outer   **Described:** M. Goldman, K. Rankin 6/1/15
Landcover: Crop   **Water Table:** not recorded
Drainage Class: WD   **Texture Group:** Fine

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
38	L	16	10YR 4/3			
56	L	24	2.5Y 5/6			
70	CL	38	10YR 5/6	5% D		
83	C	42	10YR 5/6	5% D (2% P)		
107	SiCL	36	10YR 5/6	35% P	15% 10YR 6/2	

Site: MAS 15C slope   **Described:** M. Goldman, K. Rankin 6/1/15
Landcover: Crop   **Water Table:** not recorded
Drainage Class: WD   **Texture Group:** Fine

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
41	SL	12	10YR 4/3			
51	SL	14	10YR 4/3 + 10YR 5/4			
67	L	17	10YR 5/4			
81	SiCL	32	10YR 5/6	5% D (2% P)		
102	SiCL	34	10YR 5/6	15% D (5% P)		

Site: MAS 15D rim   **Described:** M. Goldman, K. Rankin 6/1/15
Landcover: Crop   **Water Table:** not recorded
Drainage Class: MWD   **Texture Group:** Coarse

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
29	SL	9	10YR 4/4			
48	SCL	23	10YR 5/6			
70	LS	5	7.5YR 5/6			
81	SCL	21	10YR 5/6	20% 2.5YR 4/8	10% 10YR 6/2	
107	SCL	21	10YR 6/1		25% 10YR 5/6 + 25%2.5YR 4/8	

Site: MAS 19A depression inner   **Described:** M. Goldman, K. Rankin 6/1/15
Landcover: Crop   **Water Table:** not recorded
Drainage Class: WD   **Texture Group:** Fine

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
26	SiL	13	10YR 4/3			
36	SiL	14	10YR 4/4			
54	SiCL	31	2.5Y 5/4			
104	SiCL	37	10YR 5/4	5% D		

Site: MAS 19B depression outer   **Described:** M. Goldman, K. Rankin 6/1/15
Landcover: Crop   **Water Table:** not recorded
Drainage Class: WD   **Texture Group:** Fine

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
29	L	16	10YR 4/3			
45	L	18	10YR 5/6			
72	CL	34	10YR 5/6			
93	CL	36	2.5Y 6/4	10% P	10% 10YR 7/2	
107	SCL	21	10YR 5/8			

Site: MAS 19C slope   **Described:** M. Goldman, K. Rankin 6/1/15
Landcover: Crop   **Water Table:** not recorded
Drainage Class: WD   **Texture Group:** Fine

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
28	SL	12	10YR 4/3			
58	SL	17	10YR 4/4			
77	SCL	21	10YR 5/6			
101	CL	28	10YR 5/6	5% D (2% P)		

Site: MAS 19D rim   **Described:** M. Goldman, K. Rankin 6/1/15
Landcover: Crop   **Water Table:** not recorded
Drainage Class: WD   **Texture Group:** Coarse

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
27	SL	7	10YR 4/3			
44	SL	11	10YR 5/4			
60	SL	13	10YR 5/6			
72	L	18	10YR 5/6			
98	L or SiL	16	10YR 5/6	10% D		
107	S	3	10YR 5/6			

Site: MAS 9A depression inner   **Described:** M. Goldman, K. Rankin 6/12/15
Landcover: Crop   **Water Table:** not recorded
Drainage Class: WD   **Texture Group:** Fine

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
24	SiL	12	2.5YR 4/4			
93	SiL	22	2.5YR 4/4			clay increases gradually from top from 20 to 24%
102	SiL	24	2.5YR 4/3			

Site: MAS 9B depression outer   **Described:** M. Goldman, K. Rankin 6/12/15
Landcover: Crop   **Water Table:** not recorded
Drainage Class: WD   **Texture Group:** Coarse

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
25	L	14	10YR 4/4			
67	L	17	10YR 4/4			gradual increase to bottom
102	SiL	17	10YR?			
110	SiL	21	10YR 3/3			

Site: MAS 9C slope   **Described:** M. Goldman, K. Rankin 6/12/15
Landcover: Crop   **Water Table:** not recorded
Drainage Class: WD   **Texture Group:** Fine

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
36	SL	10	10YR 4/4			
53	SL	14	10YR 5/6			
74	SL	19	10YR 5/6			
89	SCL	25	7.5YR 5/6	10% Fe masses		masses 2.5YR 4/6
100	SCL	33	7.5YR 5/6	10% Fe masses		

Site: MAS 9D rim   **Described:** M. Goldman, K. Rankin 6/12/15
Landcover: Crop   **Water Table:** not recorded
Drainage Class: WD   **Texture Group:** Fine

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
25	SiL	20	10YR 4/4			
50	L	27	10YR 5/6			
76	SL	18	10YR 5/6			
100	SL	19	10YR 5/6			

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Site: OVW 5A depression inner   **Described:** M. Goldman, K. Rankin 6/4/15
Landcover: Crop   **Water Table:** not recorded
Drainage Class: PD   **Texture Group:** Fine

Comments: Probably originally VPD

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
23	SiL	14	2.5Y 4/3	10% D along roots	3% 10YR 6/1	
36	L	25	2.5Y 4/3	10% D along roots		
44	L	24	10YR 6/1	5% D along roots		
55	SiCL	28	10YR 6/1	25% P		
69	SiC	44	10YR 6/1	25% P		
83	L	26	5Y 6/1	15% P		
100	SiC	43	5Y 6/1	10% P		

Site: OVW 5B depression outer   **Described:** M. Goldman, K. Rankin 6/4/15
Landcover: Crop   **Water Table:** not recorded
Drainage Class: PD   **Texture Group:** Fine

Comments: probably originally VPD

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
25	iL	15	2.5Y 4/3	5% D along roots		
40	L	24	2.5Y 6/1	5% D along roots		
50	CL	28	5Y 6/1	15% P		
75	CL	29	5Y 7/1	20% P		3% chert gravels
88	CL	30	5Y 7/1	25% P		3% gravels
97	C	45	5Y 7/1	15% P		3% gravels
104	SCL	23	5Y 7/1	10% P		coarse white grains shell fragments

Site: OVW 5C slope   **Described:** M. Goldman, K. Rankin 6/4/15
Landcover: Crop   **Water Table:** not recorded
Drainage Class: PD   **Texture Group:** Fine

Comments: probably originally VPD

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
29	SL	14	2.5Y 4/3			
47	L	18	2.5Y 4/2	2% along roots		
60	CL	28	2.5Y 5/1	10% P		
83	CL	36	2.5Y 5/1	20% P		
94	L	26	5Y 6/1	30% P		
102	CL	28	5Y 7/1	25% P		

Site: OVW 5D rim   **Described:** M. Goldman, K. Rankin 6/4/15
Landcover: Crop   **Water Table:** not recorded
Drainage Class: WD   **Texture Group:** Coarse

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
21	SiL	13	10YR 4/3			
36	SiL	16	10YR 4/6			
49	CL	29	10YR 4/6			
64	L	23	10YR 4/6			5% gravel
71	SL	14	10YR 5/6			15% gravel
100	LS	6	10YR 5/6			5% gravel

Site: OVW 2A depression inner   **Described:** M. Goldman, K. Rankin, C. Seitz 6/12/15
Landcover: Crop   **Water Table:** not recorded
Drainage Class: PD   **Texture Group:** Fine

Comments: probably originally VPD

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
25	SiL	15	10YR 4/3	5% D along roots		
44	SiL	14	10YR 3/2		5% 10 YR 4/2 starting at 30 cm	
54	SiL	26	2.5Y 7/1	10% D		
60	SiL	26	2.5Y 7/1	15% P		
72	SiCL	36	2.5Y 6/1	30% P		
85	SiC	41	5Y 6/1	45% P		
105	SiC	44	5Y 6/1	20% P		

Site: OVW 2B depression outer   **Described:** M. Goldman, K. Rankin, C. Seitz 6/12/15
Landcover: Crop   **Water Table:** not recorded
Drainage Class: PD   **Texture Group:** Fine

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
26	L	14	10YR 4/3			
43	L	26	2.5Y 6/2	10% D		
54	CL	29	2.5Y 6/1	20% P		
63	CL	32	2.5Y 6/1	25% P		
92	SCL	24	2.5Y 7/1	30% P		
106	L	16	5Y 7/1	35% P		

Site: OVW 2C slope   **Described:** M. Goldman, K. Rankin, C. Seitz 6/12/15
Landcover: Crop   **Water Table:** not recorded
Drainage Class: WD   **Texture Group:** Coarse

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
21	SL	13	10YR 4/3	5% D starts at 13 cm		
39	SCL	23	10YR 5/6			
46	SCL	28	10YR 5/6			
66	SL	15	10YR 5/8			
92	LS	8	10YR 5/8			
102	S	6	10YR 5/8			

Site: OVW 2D rim   **Described:** M. Goldman, K. Rankin, C. Seitz 6/12/15
Landcover: Crop   **Water Table:** not recorded
Drainage Class: WD   **Texture Group:** Coarse

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
40	L	11	10YR 3/2			
55	CL	30	10YR 4/4	20% D		
70	SCL	25	10YR 4/4	10% D		
100	LS	8	10YR 5/6	15% D		

Site: OVW 7A depression inner   **Described:** M. Goldman, K. Rankin, C. Seitz 6/12/15
Landcover: Crop   **Water Table:** not recorded
Drainage Class: VPD   **Texture Group:** Fine

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
19	SiL	25	10YR 3/2			
42	SiCL	36	2.5Y 6/1	20% P		
63	SiCL	34	2.5Y 7/1	15% P		
81	SiCL	28	5Y 6/1	15% P		
100	C (SiC)	41	5Y 6/1	20% P		
103	C	42	5Y 6/1	20% P		

Site: OVW 7B depression outer   **Described:** M. Goldman, K. Rankin, C. Seitz 6/12/15
Landcover: Crop   **Water Table:** not recorded
Drainage Class: PD   **Texture Group:** Fine

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
20	SiL	17	10YR 4/3			
30	SiL	17	10YR 4/2	2% D	2% 2.5Y 6/2	
42	SiL	25	10YR 4/2	2% D	5% 2.5Y 6/2	
62	SiCL	29	2.5Y 6/1	15% P		
74	CL	33	5Y 6/1	25% P		
82	SCL	25	5Y 6/1	15% P		
102	LS	7	5Y 6/1	2% P		

Site: OVW 7C slope **Described:** M. Goldman, K. Rankin, C. Seitz 6/12/15
Landcover: Crop **Water Table:** not recorded
Drainage Class: VPD **Texture Group:** Fine

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
23	L	15	10YR 3/2			
33	L	13	10YR 3/2		5% 10YR 6/1	
48	SCL	23	2.5Y 6/1	10% P		
69	SCL	22	10YR 6/1	40% P		
77	SCL	20	2.5Y 7/1	35% P		
96	SL	19	2.5Y 7/1	15% P		
107	SCL	26	5Y 7/1	5% P		

Site: OVW 7D rim **Described:** M. Goldman, K. Rankin, C. Seitz 6/12/15
Landcover: Crop **Water Table:** not recorded
Drainage Class: SWPD **Texture Group:** Coarse

Comments:

Depth	Texture	Clay %	Color	Conc.	Depl.	Comments
37	SL	11	2.5Y 4/2			
71	LS	7	2.5Y 6/2			
87	SL	19	2.5Y 6/2	30% P		
110	SCL	22	10YR 7/1	30% P		

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