ABSTRACT

Title of Thesis:	USING LANDSCAPE METRICS TO PREDICT HYDROLOGIC CONNECTIVITY PATTERNS BETWEEN FORESTED WETLANDS AND STREAMS IN A COASTAL PLAIN WATERSHED
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Geographically isolated wetlands, those entirely surrounded by uplands, provide numerous ecological functions, some of which are dependent on the degree to which they are hydrologically connected to nearby waters. There is a growing need for field-validated, landscape-scale approaches for classifying wetlands based on their expected degree of connectivity with stream networks. During the 2015 water year, flow duration was recorded in non-perennial streams (n = 23) connecting forested wetlands and nearby perennial streams on the Delmarva Peninsula (Maryland, USA). Field and GIS-derived landscape metrics (indicators of catchment, wetland, non-perennial stream, and soil characteristics) were assessed as predictors of wetland-stream connectivity (duration, seasonal onset and offset dates). Connection duration was most strongly correlated with non-perennial stream geomorphology and wetland characteristics. A final GIS-based stepwise regression model (adj-R^2 = 0.74, $p < 0.0001$) described wetland-stream

connection duration as a function of catchment area, wetland area and number, and soil available water storage.

USING LANDSCAPE METRICS TO PREDICT HYDROLOGIC CONNECTIVITY
PATTERNS BETWEEN FORESTED WETLANDS AND STREAMS IN A COASTAL
PLAIN WATERSHED

by

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Dedication

For Emmanuel Ayompe, who left his home in Cameroon in pursuit of an education and greater opportunities in the United States. Your tireless ambition and positivity in the face of adversity is both inspiring and humbling.

Acknowledgements

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INTRODUCTION

Wetlands are unique hydrologic features on the landscape that occupy a transition zone between predominantly wet and dry environments (Tiner 2010). A wetland's position within this transition zone is variable; wetland hydrologic behavior (e.g., water stage, inundation period) is influenced by net inflows and outflows from ground, surface, and atmospheric water (Tiner 2010). Attributed in large part to these dynamics, wetlands perform a number of important functions on the landscape, classified broadly as hydrologic, biogeochemical, and habitat/food web support (Sharitz 2003). Past studies indicate that some wetland functions are dependent on the degree to which waters are hydrologically connected to nearby waters (Leibowitz 2003). Identifying drivers of hydrologic connectivity is a necessary step in quantifying the degree of connectivity between wetlands and other aquatic features at the landscape scale (Cook and Hauer 2007, Yuan et al. 2014), a critical determinant of the protection status of many wetlands within the United States (U.S.) (Nadeau and Rains 2007, Alder 2015).

Defining "hydrologic connectivity"

Landscape connectivity (Taylor et al. 1993) has long been recognized as an important concept in spatial ecology and conservation biology. Two landscape features can be considered connected whenever a path exists between them (Matisziw et al. 2015); *hydrologic connectivity* has been explicitly defined as the "water-mediated transfer of matter, energy and/or organisms within or between elements of the hydrological cycle" (Pringle 2001). Wetland functions associated with varying degrees of hydrologic

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connectivity influence the watershed integrity by supplying beneficial materials (source function), removing harmful materials (sink function), providing habitat and preventing removal of beneficial materials (refugia function) (Leibowitz et al. 2008). For example, longer hydroperiods and occasional surface water connections to permanent waters have been linked to higher species richness (Snodgrass et al. 1996) and higher net primary productivity (Cook and Hauer 2007) in seasonal wetlands. Wetland area within a watershed has been shown to be significantly related to flood control (Mitsche and Gosselink 2000, Lindsay et al. 2004) and reduced nitrate concentrations in groundwater and surface water (Phillips et al. 1993).

Drivers of wetland-stream hydrologic connectivity

In its most general sense, hydrologic connectivity describes all positions, and times, associated with the movement of water through a point in the landscape (Bracken and Croke 2007). Hydrologic connectivity is therefore influenced by both static (e.g., spatial patterns) and dynamic (e.g., antecedent rainfall conditions) processes (Bracken and Croke 2007). Hydrologic response (e.g., runoff response time) at the catchment scale is, in part, a function of landscape structure, in particular the spatial relationship between runoff-generating areas, flow pathways, and the catchment outlet (Nippgen et al. 2011, Shaw et al. 2013, Ali et al. 2015). Wetlands, at times runoff-generating areas, are dynamic features whose position along the connectivity continuum (Leibowitz 2003) is influenced in part by their hydrologic relationship to atmospheric and groundwater sources and sinks (Euliss et al. 2004).

In addition to natural structures and processes, human perturbations can reduce or enhance hydrologic connectivity (Pringle 2003). Extensive dam infrastructure has

contributed to the fragmentation of more than 98% of the 5.2 million kilometers of streams in the U.S. (Benke 1990). Urban development has led to the complete loss of many upland wetlands while channelization and other forms of development have resulted in the hydrologic disconnection of many riparian wetlands from streams and wetlands (Zedler and Kirshner 2005, Theriot et al. 2013). Agricultural drainage through ditching and tile drainage has not only led to the greatest loss of wetlands globally (e.g. Blann et al. 2009, Bartzen et al. 2010) but can also result in decreased hydrologic or biotic connectivity among remaining wetlands in some regions (Leibowitz and Nadeau 2003). Even with the loss of many wetlands, recent use of high resolution imagery has shown that the remaining wetlands and small streams on ditched agricultural lands may be far greater than previously thought (Lang et al. 2012) and the plugging of ditches to restore wetlands results in even greater surface hydrologic connectivity (McDonough et al. 2014).

Regulatory needs for quantifying wetland-stream connectivity at the landscape scale

In the past few decades, growing attention has been placed on defining concepts related to connectivity in the United States (U.S.) as they pertain to the federal protection of waters. In its rulings on challenges to U.S. Clean Water Act (CWA) jurisdiction over "isolated" waters, the U.S. Supreme Court stated that wetlands and ponds having a "significant nexus" to "traditional navigable waters" may be eligible for federal protection under the CWA. In 2015, the United States Environmental Protection Agency (USEPA) and United States Army Corps of Engineers (USACE) finalized a rule to more explicitly define the jurisdictional extent of the CWA in light of the Court's rulings (USEPA and USACE 2015). This rule, titled the Clean Water Rule, identifies six

categories of waters that are jurisdictional in all cases, without the need for further analysis. Two additional categories of waters may be afforded CWA protection where a case-specific determination finds a "significant nexus" between the water(s) in question and traditional navigable waters, interstate waters, or territorial seas (Alexander 2015). Based on a review and synthesis of scientific evidence (USEPA 2015) the regulatory agencies concluded that the cumulative effects of individual streams and wetlands across time and space should be considered when assessing their effects on downstream waters. The agencies further determined that it is reasonable to consider waters as "similarly situated" where they function alike and are sufficiently close to function as a system in affecting the nearest jurisdictional water. Based on the available scientific evidence, five subcategories of waters (prairie potholes, Delmarva and Carolina Bays, pocosins, western vernal pools in California, and Texas coastal prairie wetlands) were determined to be "similarly situated" by rule and, thus, must be considered in combination in any jurisdictional determination of "significant nexus" (USEPA and USACE 2015). To further inform regulations, several of these five, including Delmarva Bays which are the focus of this study, have sites with significant ongoing research to increase scientific understanding of the ecological importance of hydrologic connectivity.

Delmarva Bays

Delmarva bays are depressional wetlands that occur throughout the U.S. Atlantic Coastal Plain, regionally referred to as Carolina bays in the southeastern U.S. and Delmarva potholes in the Mid-Atlantic region. Tiner (2003) classified them as geographically isolated wetlands (wetlands that are completely surrounded by uplands; see also Mushet et al. 2015), as they characteristically lack permanent natural surface

water drainages into or from them, resulting in a hydrology driven primarily by seasonal patterns of precipitation, evapotranspiration and surface water-groundwater interactions (Sharitz 2003, Ator et al. 2005, Pyzoha et al. 2008). The hydrology of Delmarva bays is intimately related to groundwater dynamics. McDonough et al. (2014) suggest that seasonal, intermittent surface hydrologic connections between forested Delmarva bays and nearby perennial streams are driven primarily by groundwater processes. Delmarva bays can store water from groundwater discharge during the wet season and then reverse flow and recharge regional groundwater during the dry season (Tiner 2003). At the watershed scale, the distribution and density of geographically isolated wetlands (GIWs) can thus influence groundwater flow dynamics and annual baseflow patterns in downstream waters (Evenson et al. 2015).

The most strongly supported theory of Delmarva bay formation is that they began as wind blowouts during the Pleistocene epoch that became locations where the water table was above the surface (Prouty 1952, Fenstermacher et al. 2014). Fenstermacher et al. (2014) estimate that there are 17,000 bays across the Delmarva Peninsula at a median density of 2.02 bays km^{-2}, though they can cover as much as 50 percent of the land area in areas where they are found (Prouty 1952, Fenstermacher et al. 2014), frequently forming wetland complexes (Sharitz and Gibbons 1982). Bay size varies regionally, from a mean area of 2.83 hectares (ha) on the Delmarva Peninsula (Fenstermacher et al. 2014) to 46 ha among Carolina bays in South Carolina.

Despite their classification as "geographically isolated", most depressional wetlands on the Delmarva Peninsula contain shallow, hand dug ditches created in the early to mid-1900s to drain them for agriculture; a smaller portion contains deeper

(>1.5m) ditches that are currently maintained (Lang et al. 2013) (Fig. 1). Based on visual

analysis, Fenstermacher et al. (2014) concluded that only 29% of Delmarva bays on the

Delmarva Peninsula currently appear "natural" (i.e., covered by undisturbed vegetation,

generally forested areas and herbaceous areas surrounded by forest), and that most of

these bays have likely undergone some hydrological disturbance, such as man-made

drainage.
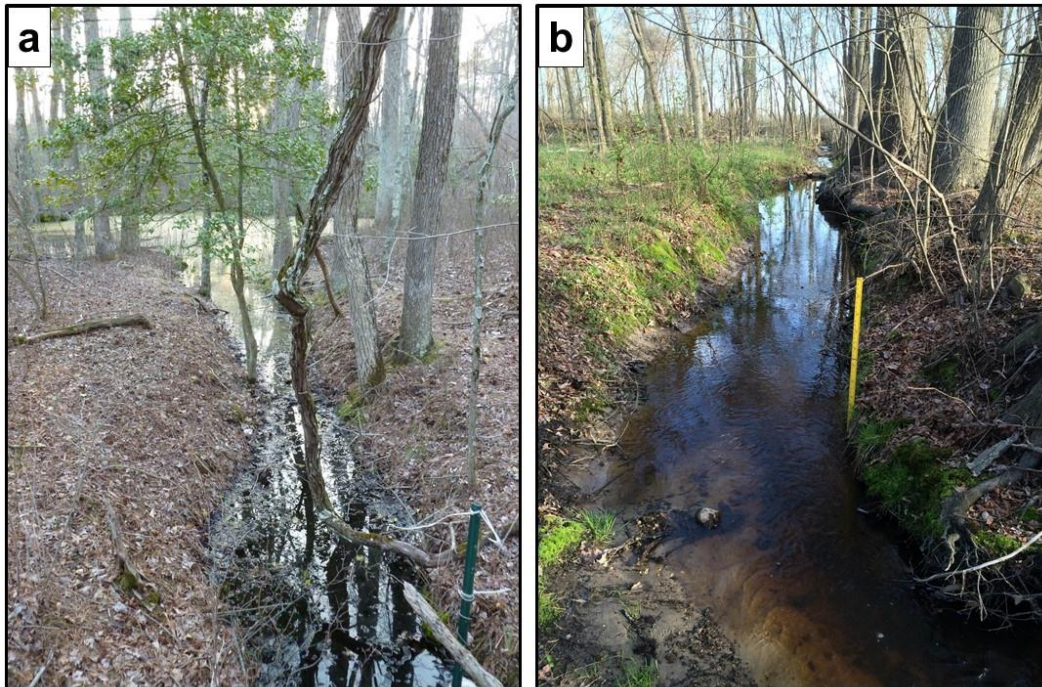
Figure 1. Non-perennial streams connect many forested wetlands to downstream
perennial waters via surface flow. Dates pictured: 12 Apr 2014 (a), 19 Apr 2014 (b)

Study Goals and Objectives

This research sought to advance our understanding of the relationship between

landscape characteristics and the hydrologic connectivity between forested Delmarva Bay

wetlands and the surrounding stream network. The ability to predict the position and level

of connectivity would be a major advance and could provide an important tool for

managers and regulators. To date, most studies have relied on Euclidean distance-based

techniques using nationally-available stream and wetland datasets to assess wetland-stream connectivity, where all wetlands that fall within a specified distance from a stream channel are assumed to be connected to the drainage network (Fig. 2). Lane et al. (2012) used 10-m buffered United States Geological Survey National Hydrography Dataset (NHD) streams (1:24,000 scale) and the National Wetlands Inventory (NWI) dataset to estimate wetland-stream connectivity across an eight-state region of the southeastern mid-Atlantic U.S. They found that 9% of freshwater habitat is potentially geographically isolated wetlands. Lang et al. (2012) used a semi-automated stream mapping approach, based on light detection and ranging (LiDAR) digital elevation maps, to estimate connectivity with state-surveyed wetland polygons within a Coastal Plain watershed (Maryland, U.S.). They report that 53% of semi-natural wetlands (by total number) were directly connected to streams and 60% were stream-connected using a 10-m stream buffer. Given the extent of artificial wetland drainage in these areas, both estimates are likely to be highly conservative. Lang et al. (2012) also noted that the difficulty of mapping small ditches in low topographic relief settings may have led to underestimates of wetland hydrologic connectivity.

While distance-based methods may provide a reasonable first-order estimation of physical wetland-stream connectivity at the regional or national scale, more accurate approaches are needed to predict surface hydrologic connectivity (SHC) at smaller catchment scales. Paired with a mechanistic understanding of the drivers of local hydrology, recent advancements in remote sensing and GIS-based methods provide an opportunity to more accurately map streams, wetlands, and predict the relative degree of connectivity between water features across the landscape. The goal of this study was to

develop such an approach using field and GIS-derived landscape predictor metrics
representing drivers of stream flow permanence.

The specific objectives of this study are: (1) quantify temporal variability in SHC
patterns between forested wetlands and perennial streams from field observations over
the 2015 water year; (2) develop predictive metrics representing hypothesized landscape
drivers of wetland-stream SHC; and (3) model cumulative SHC duration, seasonal
connection onset dates, and seasonal connection offset dates as a function of landscape
predictor metrics.
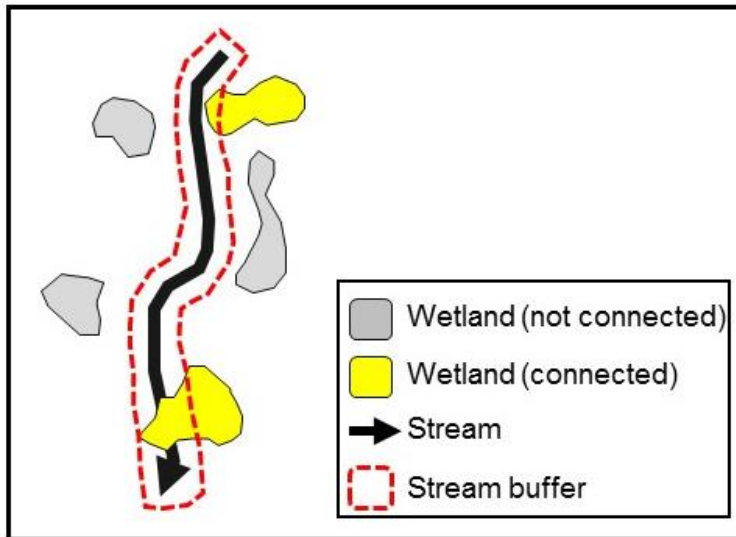
Figure 2. Schematic of distance-based wetland-stream connectivity analysis. Streams are
usually first buffered to account for dataset spatial accuracy

METHODS

Temporal patterns in SHC were quantified from float switch state loggers placed in non-perennial streams that connected forested wetlands to nearby perennial streams on the Delmarva Peninsula of Maryland, USA. Landscape metrics representing hypothesized drivers of SHC were developed using both field and GIS-based techniques. The utility of individual and sets of landscape metrics in predicting measures of connectivity (cumulative SHC duration, seasonal connection onset date, seasonal connection offset date) was assessed using stepwise linear regression modeling.

Study Sites

The Coastal Plain study sites were within the Choptank River watershed (1,756 km^2) and the neighboring Corsica River watershed (102 km^2), which drain portions of Maryland and Delaware (U.S.) to the Chesapeake Bay. Land use in the Choptank River watershed is dominated by agriculture (60%) and forest (33%) (McCarty et al. 2008). Similar land uses have been reported in the Corsica River watershed: 60% agriculture, 25% forest, 5% urban areas (Maryland Department of the Environment 2011). Twenty-three forested wetland catchments situated across a 150 km^2 area within the Choptank River (n = 21) and the Corsica River (n = 2) watersheds were selected for this study (Fig. 3). Given this study's focus on forested wetlands, study sites were selected in and around the upper portion of the Choptank River watershed where there are tracts of state (e.g., Maryland Department of Natural Resources) or conserved (e.g., The Nature Conservancy) forested lands.
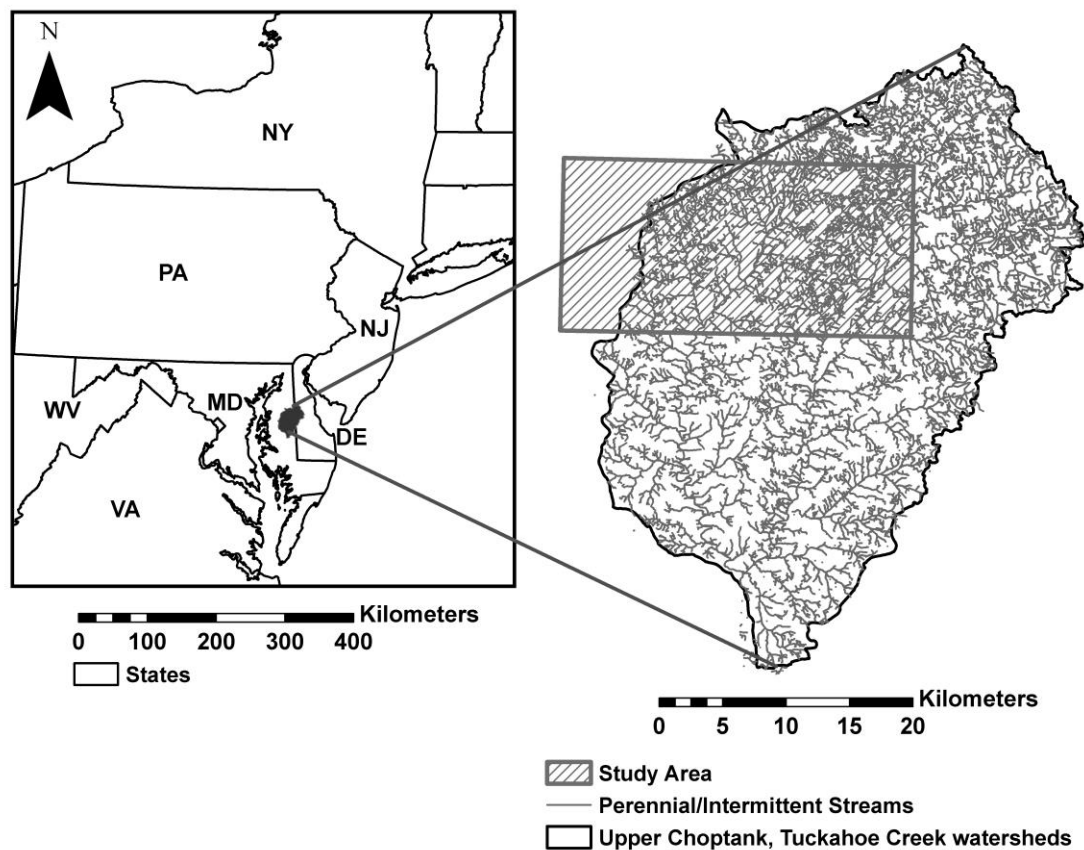
Figure 3. Location of the study area within the upper portions (Upper Choptank, Tuckahoe Creek) of the Choptank River watershed

The hydrology of the Mid-Atlantic Coastal Plain region, represented by long-term (seasonal) and short-term (daily) stream discharge patterns, is controlled by rainfall, temperature, evapotranspiration, topography, and soil drainage properties (Fisher et al. 2010). Annual precipitation (117 cm $\pm$ 4.2 cm (mean $\pm$ SE)) is distributed uniformly throughout the water year (1986 – 2015 at Goldsboro, MD; PRISM climate mapping system [www.prism.oregonstate.edu]). Approximately 50% of annual precipitation is lost to the atmosphere via evapotranspiration while the remainder recharges ground water or enters streams via surface runoff (Leahy and Martin 1993). From approximately April to

August, evapotranspiration and streamflow discharge rates exceed rainfall, leading to net water loss and falling groundwater levels (Fisher et al. 2010). Surface water levels reach peak expression in early spring (March/April) when levels of evapotranspiration are still relatively low (Lang et al. 2012).

In this study, forested wetland catchments are defined as the total contributing area draining one or more forested Delmarva bay wetlands to the perennial stream network via seasonal surface flow. Resulting in part from human perturbations (e.g., ditching), most forested wetlands examined in this study connected seasonally to the perennial stream network via surface flow (Fig. 4). Forested wetland catchment outlets (non-perennial/perennial stream confluence points) were first identified within ArcGIS (ESRI; Redlands, CA) using a 2m digital elevation model (DEM) flow accumulation layer to find contributing areas immediately upstream of the perennial stream network (Lang et al. 2012). Field visits with a handheld GPS unit (Trimble Geo 7x model) were then conducted to validate catchment outlet locations, and assess the eligibility of each site for long-term monitoring. Land access proved to be the prohibitive factor among most potential study sites. Most catchments in this study (n = 14) were selected because of the ability to monitor the non-perennial/perennial stream confluence at road crossings; the remaining catchments (n = 9) were located on state [Maryland Department of Natural Resources (DNR)], conserved (The Nature Conservancy), or private lands with explicit permission from landowners.
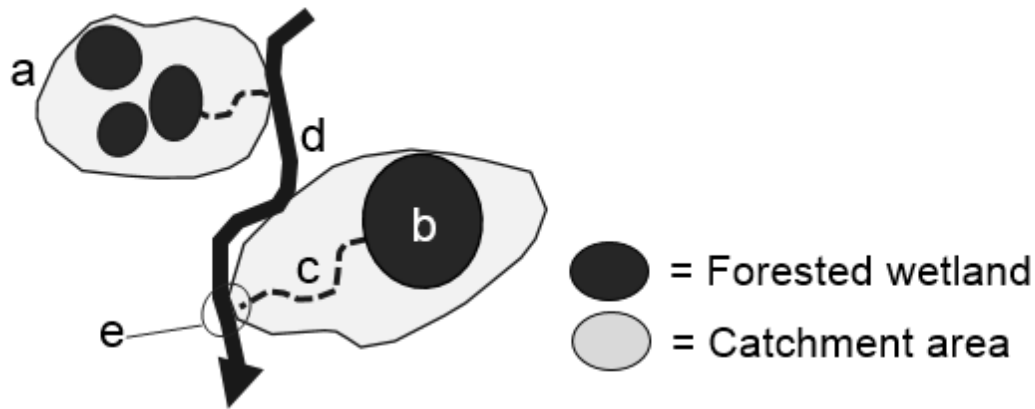
Figure 4. Schematic of forested wetland catchments, defined as relatively small areas of predominantly forested (generally, > 50% forested) land (a) comprised of one or more seasonally-inundated Delmarva bays (b) that produce episodic surface outflow into non-perennial streams (c), connecting them to the perennial stream network (d). Catchment outlets were defined as the non-perennial/perennial stream confluence (e)

A hand-edited, flow accumulation-based stream dataset developed by Lang et al. (2012) was used to represent the perennial stream network for the Choptank River watershed. For the present study, their methods were applied for the Corsica River watershed since it watershed extended beyond the spatial coverage of Lang et al.'s existing data layer. Briefly, the Lang et al. (2012) method included using ArcGIS ArcHydro (ESRI; Redlands, CA) tools to automatically delineate stream networks at a flow accumulation threshold of 30 ha then hand-editing using several recent leaf-on and leaf-off aerial images to include only streams that met a minimum set of criteria (e.g., water appeared to be present within the channel within the last decade, a vegetation buffer was present around the channel). The resulting stream datasets include only streams judged to be perennial or intermittent and therefore groundwater fed at some point during a year of normal precipitation.

Precipitation

Historical monthly rainfall totals (1986 – 2015) were calculated using PRISM climate mapping system data (www.prism.oregonstate.edu, downloaded on 13 Oct 2015). Briefly, PRISM (Parameter-elevation Regressions on Independent Slopes Model) applies a regression-based approach using climate station point data, a DEM and other spatial datasets, and an encoded spatial climate knowledge base to predict climate (e.g., precipitation, temperature) across a gridded landscape. A linear climate-elevation relationship, in which slope changes locally with elevation, is applied at each DEM grid cell, with the assumption that elevation is the principle driver of temperature and precipitation distribution. The climate data are obtained from stations (13,000 stations across the conterminous U.S.) and weighted to control for the effects of additional variables, such as proximity to nearby stations, topographic position, and coastal proximity (Daly et al. 2008). For this study PRISM 4km grid data were used to estimate daily rainfall totals at each forested wetland catchment during the 2015 water year.

Field-based hydrologic connectivity monitoring

Surface flow in non-perennial streams connecting forested wetlands to nearby perennial streams was recorded continuously over the 2015 water year (1 Oct 2014 to 30 Sep 2015). A float switch state data logger was positioned in the thalweg of each non-perennial stream bed at the maximum longitudinal elevation along the channel, to avoid local pools where standing water could falsely indicate the presence of surface flow. Loggers were designed according to McDonough et al. (2014), with a binary polypropylene float switch (SMD Fluid Switch, Wallingford, CT) connected to a state data logger (HOBO model UX90-001; Onset Computer Corp., Bourne, MA) (Fig. 5).

Surface water presence in maximum elevation areas within non-perennial streams was generally assumed to indicate a surface hydrologic connection between wetlands and nearby perennial streams.
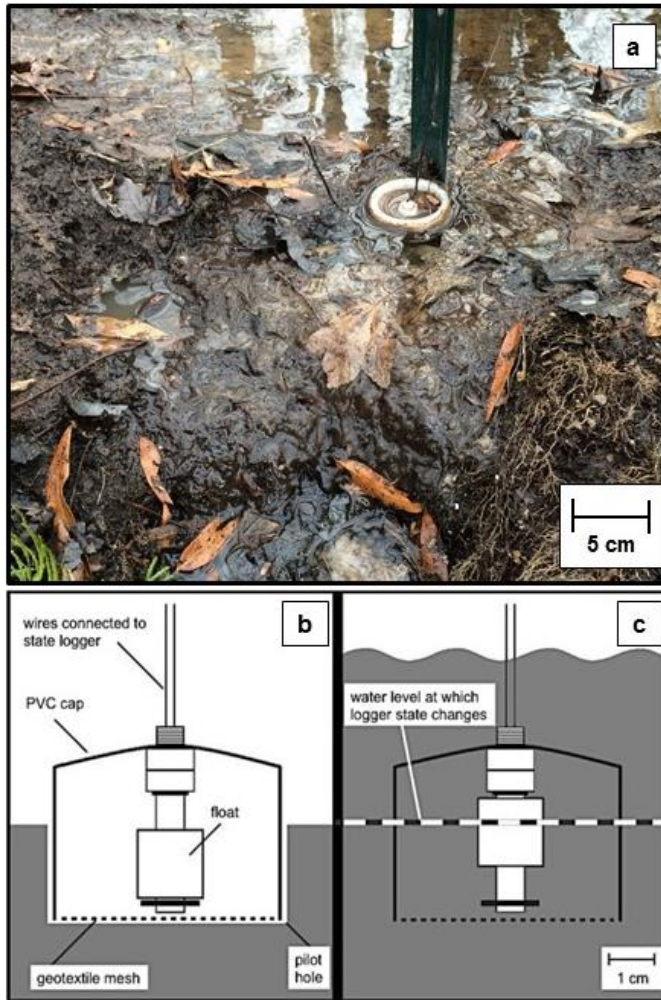
Figure 5. Float switch state logger placed in the center of non-perennial stream bed (a). Logger was comprised of a buoyant polypropylene float switch connected to a state data logger to record periods of no flow (b) and flow (c). Schematic of float switch (b, c) from Figure 4, McDonough et al. (2014); reprinted with kind permission from Springer Science and Business Media

Biweekly (November 2014 – May 2015) or monthly (October 2014, June 2015 – October 2015) site visits were made to validate or modify state data logger readings. At each site visit, discharge ($L\ s^{-1}$) was measured with a Hach FH950 (Hach Co, Loveland,

CO) portable velocity meter with electromagnetic sensor) using the cross-sectional area method (Fritz et al. 2006).

For each catchment, state data logger records were used to generate three measures of connectivity over the 2015 water year: (1) *cumulative connection duration*, defined as the total number of days that wetlands connected to nearby perennial streams via surface flow; (2) *seasonal connection onset date*, defined as the Julian date of the first $\geq$ 24 hour connection event; and (3) *seasonal connection offset date,* defined as the Julian date of the last $\geq$ 24 hour connection event during the 2015 water year.

Landscape predictor metrics

Winter's (2001) hydrologic landscape conceptual framework was used to develop landscape predictor metrics representing the hypothesized drivers of hydrologic connectivity, from field and GIS-derived landscape variables generated at the reach and catchment scales (Table 1). Briefly, Winter's (2001) framework describes hydrologic landscapes on the basis of land-surface form, geology, and climate, which can be used to develop hypotheses of how the hydrologic system might function in those terrains. This and similar frameworks have provided a foundation for classifying stream reaches (Svec et al. 2005, Bent and Steeves 2006, Fritz et al. 2008), watersheds (Winter 2001), and regions (Wolock et al. 2004, Ator et al. 2005) based on physical and hydrologic characteristics. This study used metrics characterizing land-surface form and geology of catchments since climate conditions are similar across the study area. Metrics were classified into four groups based on the scale and landscape feature represented: catchment, non-perennial stream, wetlands, and soils. Two major considerations motivated final selection of GIS data layers with used to generate landscape predictor

metrics: (1) the need to detect fine-scale variability between study catchments ranging in area from < 1 ha to more than 70 ha, and (2) data layers with spatial coverage across the Upper Choptank, Tuckahoe Creek, and eastern portion of the Corsica River watersheds (1,069 km^2) to be useful in watershed-wide SHC predictions.

Landscape predictor metric development and spatial analyses were conducted using: ArcGIS (version 10.1; ESRI, Redlands, CA), R (version 3.2.2; R Development Core Team 2015), and Geospatial Modelling Environment (Beyer 2012).

Catchment metrics

Catchment metrics were generated using a light detection and ranging (LiDAR) based 2m digital elevation model (DEM). The LiDAR data used to derive this DEM were collected for the Maryland DNR during spring 2003 and spring 2006 (metadata available at: http://dnrweb.dnr.state.md.us/gis/data/lidar/). These datasets had a vertical accuracy of ≤ 18 cm root mean square error (RMSE) and were designed to meet or exceed Federal Geographic Data Committee (1998) National Standards for Spatial Data Accuracy standards for data at 1:2,400. Estimated horizontal positional accuracy of LiDAR point returns exceeds 50 cm. Bridges, roads and other impediments to two-dimensional flow were eliminated, then bare earth LiDAR point data were rasterized to create a 2-meter resolution DEM using inverse weighted distance interpolation.

Terrain analysis of high resolution digital elevation data is being increasingly used as a method for automated delineation of flow paths, watersheds, and flow networks (Tarboton and Ames 2001). Briefly, DEM sinks (cells completely surrounded by higher elevation cells) are filled to create a depressionless DEM, flow direction is assigned to each grid cell in the direction(s) of steepest elevation descent, and flow accumulation is

calculated across the DEM, where cell values denote the number of upslope cells flowing into that cell. A flow accumulation threshold is then applied to define stream channels, and catchments are delineated by identifying all grid cells contributing surface flow to a given outlet point.

Catchment areas were calculated based on the D8 flow routing algorithm using the Terrain Analysis Using Digital Elevation Models (TauDEM) software version 5.3 (Tarboton 1997). Catchment outlets were defined as the highest flow accumulation cell upstream of a non-perennial/perennial stream confluence. Locations of the state data loggers in non-perennial streams were field verified on 15 May 2015 using a handheld GPS (Trimble Geo 7x model), then snapped to the highest flow accumulation cell upstream of the non-perennial/perennial stream confluence. The Trimble Geo 7x GPS was designed to operate under a forest canopy and is capable of collecting data with sub-meter accuracy. GPS accuracy was enhanced by real-time WAAS correction and multiple (> 15) GPS readings were collected at each location to increase the positional accuracy of the data.

Catchment terrain slope was calculated using the TauDEM D∞ flow routing algorithm. *Topographic wetness index* (TWI) was calculated for each catchment cell as ln(a/tan β), where a is the upslope area per unit contour length and tan β is the D∞ slope (Beven and Kirkby 1979). *Catchment terrain slope* and *TWI* were aggregated into one value for each catchment using the catchment-wide median value. Three elevation-based metrics were calculated: *catchment relief* (the difference in elevation between the highest and lowest points in each catchment), *hypsometric index* (HI; an estimate of the relative distribution of elevation within each catchment; Willgoose and Hancock 1998), and the

elevation at catchment outlet. *Catchment shape* was defined as the catchment's

length/width ratio (Bent and Steeves 2006). *Catchment depressional storage volume*, an

estimate of total surface depressional storage, was calculated by subtracting the bare earth

DEM from the sink-filled DEM, then summing these cell elevation differences across the

catchment. *Drainage density* was defined as the channel length per unit catchment area

and was calculated by manually digitizing channel lines in each catchment using the 2m

DEM and ancillary GIS layers (leaf-off aerial imagery, flow accumulation raster) as

reference.

　　　　Forest Area, the areal percentage of forest land in each catchment, was calculated

using the most recent state land use/land cover (LU/LC) dataset available. For the

Maryland catchments, 2010 data are available from the Maryland Department of

Planning (metadata available at:

http://planning.maryland.gov/PDF/OurWork/LandUse/metadata.pdf; last accessed 23

Nov 2015). These data are based on digitization at the 1:12,000 scale using enhanced

2007 aerial imagery from the National Agriculture Imagery Program (NAIP). For the

Delaware catchments, 2012 data from the Delaware Office of State Planning

Coordination (metadata available at:

https://www.arcgis.com/sharing/rest/content/items/cc913276599f4410903b1943d4a2890

d/info/metadata/metadata.xml?format=default&output=html; last accessed 29 Nov 2015).

These data are based on digitization using 2012 color infrared orthophotographs with a

0.8 ha minimum mapping unit.

Non-perennial stream metrics

Since past studies have demonstrated that stream channel physical characteristics can serve as significant predictors of stream flow duration (Svec et al. 2005, Fritz et al. 2008, Fritz et al. 2013), non-perennial stream physical dimensions were measured at connectivity state data logger locations (04 Sep 2015) based on Fritz et al. (2006) methods. *Bankfull width* (BFW) and *bankfull depth* (BFD) were defined as the stream channel width and depth (from streambed at the thalweg) at bankfull stage, respectively. Stream *cross-sectional area* (CSA) was calculated as BFW multiplied by BFD. Stream *width:depth ratio* (WD$_{ratio}$) was defined as the ratio of BFW to BFD.

Non-perennial stream *relief* (maximum elevation difference, using 2m DEM), *length* (flowpath distance between forested wetland spill point and catchment outlet), and *slope* (stream *relief* / *length*, using 2m DEM) were calculated using stream lines GPS delineated in the field on 15 May 2015. Non-perennial stream lengths were delineated by walking upstream from each catchment outlet along the channel thalweg until the channel no longer had continuous defined bed and banks (Fritz et al. 2006).

Wetland metrics

Wetland-based metrics were generated using the most recent state wetland datasets available for the study area. The Maryland Department of Natural Resources (MD DNR) wetland map was generated using the Cowardin et al. (1979) classification system and manual photo interpretation of aerial photographs (late 1980s – early 1990s) at the 1:12,000 scale (metadata available at: ftp://dnrftp.dnr.state.md.us/public/SpatialData/Wetlands/WetlandsDNR/County/dnrwet.htm; last accessed 23 Nov 2015). The Delaware Statewide Wetland Mapping Project

(SWMP) dataset was generated by updating existing NWI and SWMP data using more

recent 2007 color infrared orthophotographs (metadata available at:

https://dataexchange.gis.delaware.gov/DataExchange/download.aspx; last accessed 29

Nov 2015). SWMP wetlands were delineated at the 1:5,000 scale, then classified

according to the Cowardin et al. (1979) classification.

Wetland area was defined as the total wetland area (excluding farmed wetlands,

Cowardin (1979) "Pf" classification) within each catchment. *Number of wetlands* was

determined by the number of MD DNR wetland polygons within each catchment. *Mean

wetland distance* and *minimum wetland distance* were calculated by determining the

Euclidean distance between each MD DNR wetland polygon centroid and the catchment

outlet.

Wetland spill threshold relief was used to estimate the wetland surface water level

needed to generate a surface hydrologic connection with the nearby perennial stream. It

was calculated using the 2m DEM as the difference in elevation between the highest

point along the non-perennial stream and the lowest point within the wetland nearest to

the catchment outlet (Fig. 6).
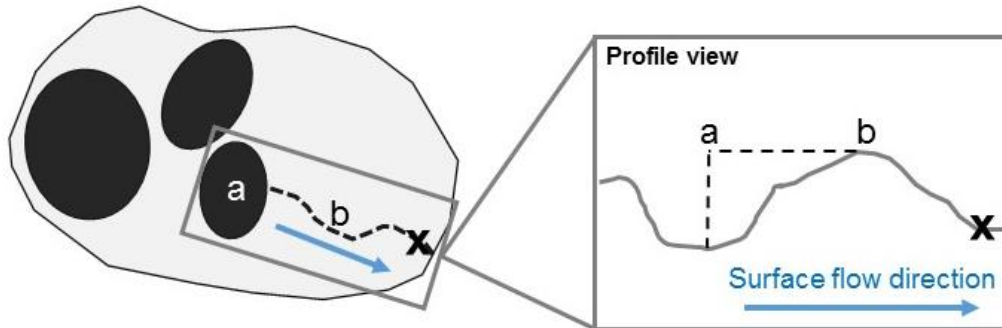
Figure 6. Wetland spill threshold relief was defined as the difference between the minimum elevation within the wetland (a) nearest to the catchment outlet (x), and the highest elevation along the non-perennial stream (b)

Cowardin et al. (1979) wetland classification includes a water regime modifier code, which describes hydrologic conditions during the growing season. Water regime values for wetlands within the study catchments ranged from saturated (substrate is saturated to the surface but typically no surface water present) to permanently flooded (water covers the land surface) (Cowardin et al. 1979). A *wetland hydrologic permanence score* was generated for each catchment by recoding wetland water regime values to a numerical scale from 1 (saturated) to 6 (permanently flooded), calculating an area-weighted mean water regime value, normalized by total wetland area.

Soil metrics

Soil-based metrics were generated using Soil Survey Geographic Database (SSURGO) soils data (version 2.2). SSURGO maps are created using manual photo interpretation at scales ranging from 1:12,000 to 1:63,630; minimum delineation size for Maryland surveys is approximately 0.6 ha. County-level soils data were downloaded from the US Department of Agriculture's Geospatial Data Gateway (https://gdg.sc.egov.usda.gov/; downloaded 18 Aug 2015), then clipped to the study area.

SSURGO soils are classified into hydrologic groups based on a soil's infiltration rate. Soil hydrologic groups range from "A" to "D", with "A" soils having a very high infiltration rate (and hence a relatively low runoff potential) and "D" soils having a very low infiltration rate (and hence a relatively high runoff potential) (NRCS 2007). In some areas, soils are assigned a dual hydrologic group status (e.g., "A/D") to indicate soil drainage properties in both "drained" (areas where seasonal high water table is kept at least 60 cm below the soil surface where it would be higher in a natural state) and "undrained" conditions, respectively. A catchment-wide *infiltration score* was calculated

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using SSURGO data representing both drained ($\text{Infil}_{\text{drained}}$) and undrained ($\text{Infil}_{\text{undrained}}$) conditions. Hydrologic group values were recoded to a numerical scale from 1 (high infiltration) to 4 (very low infiltration), then aggregated to generate one area-weighted mean catchment value.

Available water storage represented an estimate of the water volume that soil (0 – 150 cm depth) can store after having been wetted and free drainage has ceased; higher values are generally associated with low infiltration soil types (loams, clays). *Annual minimum water table depth* (WT_{depth}) represented an estimate of the shallowest depth to a wet soil layer (water table) at any time during the year. *Saturated hydraulic conductivity* represented a soil's ability to transmit water when subjected to hydraulic gradient. As with *infiltration* score, all other soils-based metrics were aggregated to generate an area-weighted mean catchment value.

Table 1. Landscape predictor metrics tested against the wetland-stream surface hydrologic connectivity metrics

Indicator Type	Predictor Metric	Description	Mean (min, max) [a]
Catchment	CatchArea [b]	Catchment area (ha)	18.6 (1.0, 71.2)
	CatchSlope	Median catchment slope (m/m)	0.046 (0.027, 0.058)
	CatchRelief	Catchment relief (m)	4.2 (1.6, 7.5)
	HI	Hypsometric index (m/m)	0.43 (0.32, 0.58)
	CatchOutElev	Elevation at catchment outlet (m)	17.3 (14.1, 21.1)
	CatchShape	Catchment length:width ratio (dimensionless, m/m)	1.6 (1.0, 2.6)
	CatchVolStorage [b, f]	Catchment depressional surface storage volume	3,135.9 (48.0, 14,714.7)
	TWI [c]	Median topographic wetness index value in catchment	0.22 (0.20, 0.25)
	Dd [b]	Drainage density (m/m^2)	1.9 (0.2, 5.7)
	Forest	Forest area (proportion of catchment)	0.79 (0.09, 1.00)
Non-perennial stream	StreamRelief [d]	Non-perennial stream relief (m)	0.02 (-0.67, 0.76)
	StreamLength [b, d]	Non-perennial stream length (m)	79.2 (5.3, 386.6)
	StreamSlope [d]	Non-perennial stream slope (m/m)	-0.001 (-0.117, 0.007)
	BFW [b, d]	Non-perennial stream bankfull width (m)	1.99 (0.86, 4.5)
	BFD [d]	Non-perennial stream bankfull depth (m)	0.30 (0.05, 0.69)
	CSA [b, d]	Non-perennial stream cross-sectional area (m^2)	0.71 (0.05, 2.46)
	WD$_{ratio}$ [b, d]	Non-perennial stream width:depth ratio (m/m)	7.56 (4.19, 18.3)
Wetlands	WetArea [b]	Wetland area (ha)	7.2 (0.2, 43.3)
	WetRelief [b]	Wetland spill relief threshold (m)	0.87 (0.38, 1.65)
	MeanWetDist [f]	Mean wetland-to-outlet distance	209.9 (0, 628.7)
	MinWetDist [f]	Minimum wetland-to-outlet distance	14.1 (0, 123.6)
	NumWet	No. wetlands (#)	6 (1, 16)
	WetInunScore [b, g]	Wetland hydrologic permanence score (numeric score, 1 to 6)	2.8 (2.0, 4.0)
Soils	Infil$_{drained}$ [b, e]	Soil infiltration rate, drained conditions (numeric score, 1 to 4)	1.98 (1.45, 3.09)
	Infil$_{undrained}$ [e]	Soil infiltration rate, undrained conditions (numeric score, 1 to 4)	3.20 (2.36, 3.99)
	WaterStorage [e]	Available water storage in from 0-150cm soil depth (cm)	19.86 (16.34, 23.18)
	WT$_{depth}$ [e]	Annual minimum water table depth (cm)	40.14 (6.05, 70.86)
	ksat [e]	Saturated hydraulic conductivity (ksat)	120.10 (24.62, 192.80)

[a] For ease of interpretability, mean, min, and max values were calculated prior to variable transformations
[b] ln(x) transformed
[c] 1/(x) transformed
[d] Field-derived
[e] Area-weighted mean
[f] Normalized by catchment area for correlations and modeling procedures; [g] Normalized by wetland area for correlations and modeling procedures

Statistical Analyses

Paired Student's t-tests (α= 0.05) were used to assess differences in mean 5-day antecedent rainfall when SHC did and did not occur between the wetland and nearby perennial stream (after McDonough et al. 2014).

Effect of seasonality on baseflow

A permutation test based on a one-way analysis of variance (ANOVA) F-statistic was used to assess the effect of seasonality on non-perennial stream baseflow discharge measurements (α= 0.05) i.e., test the null hypothesis that the distribution of discharge values, controlling for catchment, was independent of sampling month. Discharge values were log-transformed to meet assumptions of normality. The F-statistic was calculated from a one-way ANOVA comparing monthly observed baseflow discharge values collected throughout the 2015 water year (Table 3). Discharge values were then permuted (i.e., for each catchment, discharge values were randomly reassigned to another sampling month) 10,000 times; a one-way ANOVA was calculated at each permutation and corresponding F-statistic values were used to generate an F-statistic distribution. The probability of observed discharge values under the null hypothesis was then assessed by calculating the proportion of permuted F-statistic values greater than the observed F-statistic value. Data processing was conducted using the "permute" package (version 0.8-4; Simpson et al. 2015) for R (version 3.2.2; R Development Core Team 2015).

Relationship between SHC and landscape metrics

The individual relationships between SHC metrics and landscape predictor metrics were assessed using Pearson's product moment correlation tests. Landscape

predictor metrics that deviated substantially from normality based on the Shapiro-Wilk normality test were transformed by taking the natural logarithm or inverse of the metric. Spearman rank-order correlation was used in a few instances for heavily-skewed predictor metrics.

In addition to assessing the individual correlation strengths between landscape predictor metrics and SHC values, a forward stepwise linear regression approach (alpha-to-enter ≤ 0.05) was used to model SHC patterns (cumulative connection duration, connection onset date, connection offset date) as a function of the metrics. To reduce the number of predictor metrics included (Austin and Steyerberg 2015), separate stepwise regressions were first run using predictors from each of the four groups (catchment, non-perennial stream, soils, wetlands). Significant predictors from these final regression models were then combined into a single dataset to run a full, integrated stepwise regression with predictors from all four landscape predictor groups (Fig. 7). Variance inflation cofactor (VIF) values, which represent the degree to which variance of the estimated regression coefficients are inflated as compared to when the predictor metrics are not linearly related, were used to assess multicollinearity in final models (O'Brien 2007). Landscape predictor metrics with VIF less than 10 were included in final models.

Run 4 separate stepwise regressions
Each uses a different group of landscape predictor metrics to predict the specified SHC value (cumulative duration, onset date, offset date)

| Catchment | Non-perennial Stream | Soils | Wetlands |

Model   Model   Model   Model

Combine subsets of predictor metric(s) from each final regression model into a single dataset.

Combined subset of field and GIS-based landscape predictor metrics

Run 2 full stepwise regressions
(1) Using combined set of field and GIS-based landscape predictor metrics
(2) Using GIS-based predictor metrics only

Combined subset of GIS-based landscape predictor metrics

Model   Model

Compare Model Performance
For each SHC value, compare the criterion-corrected AIC values between GIS-based and GIS+Field-based models

AICc Value   AICc Value

Figure 7. Stepwise regression procedure workflow

Comparing models with field vs. GIS-based metrics

To assess model improvement with the addition of field-derived metrics, (an important consideration when field data are unavailable), two stepwise regressions were run for each SHC metric: (1) using field and GIS-derived landscape predictor metrics, and (2) using only GIS-derived metrics. Final regression models of each SHC metric were compared using the Akaike Information Criterion corrected for small sample size (AICc). Additionally, AICc results were corroborated using a Fisher's *r*-to-*z* transformation and asymptotic *z*-test to compare the correlation coefficients of observed vs. predicted values between GIS + Field and GIS-based regression models of each SHC value (Lee and Preacher 2013).

The effect of field-derived predictors on model accuracy was assessed by conducting two-sample t-tests to compare mean catchment characteristics (e.g., drainage density, bankfull width) between groups of catchments for which GIS-based models overestimated (positive residuals) and underestimated (negative residuals) SHC values. All statistical analyses were conducted in R (version 3.2.2; R Development Core Team 2015).

RESULTS

Precipitation during the 2015 water year

Total rainfall during the 2015 water year (133.0 cm) was greater than the 30-year (1986 – 2015) average (117.4 cm). Monthly rainfall totals during the 2015 water year were greater than the 30-year normals during months (Nov, Dec, Jan, Mar, Jun) when wetland-stream SHC is most likely to occur. Total 5-day antecedent rainfall was significantly greater on days when a connection event occurred compared to 5-day antecedent totals when a connection did not exist ($t = 9.07$, df $= 22$, $p < 0.001$, mean of differences $= 5.40$ mm).

Observed wetland-stream connectivity patterns

Surface flow patterns in non-perennial streams connecting forested wetlands to nearby perennial streams varied between wetland catchments (n = 23) with cumulative wetland-stream connectivity duration ranging from 64 to 298 days ($\bar{x}$ =164.6 days). Between late-spring and late-fall, patterns were characterized by short-term connections (several hours in duration) following rainfall events (Fig. 8, 9). Median seasonal connection onset and offset dates (first and last >24 hour connection) were December 9 and July 5, respectively (Table 2). Moran's I testing determined a lack of spatial autocorrelation in SHC metric values, including onset and offset dates, across forested wetland catchments.
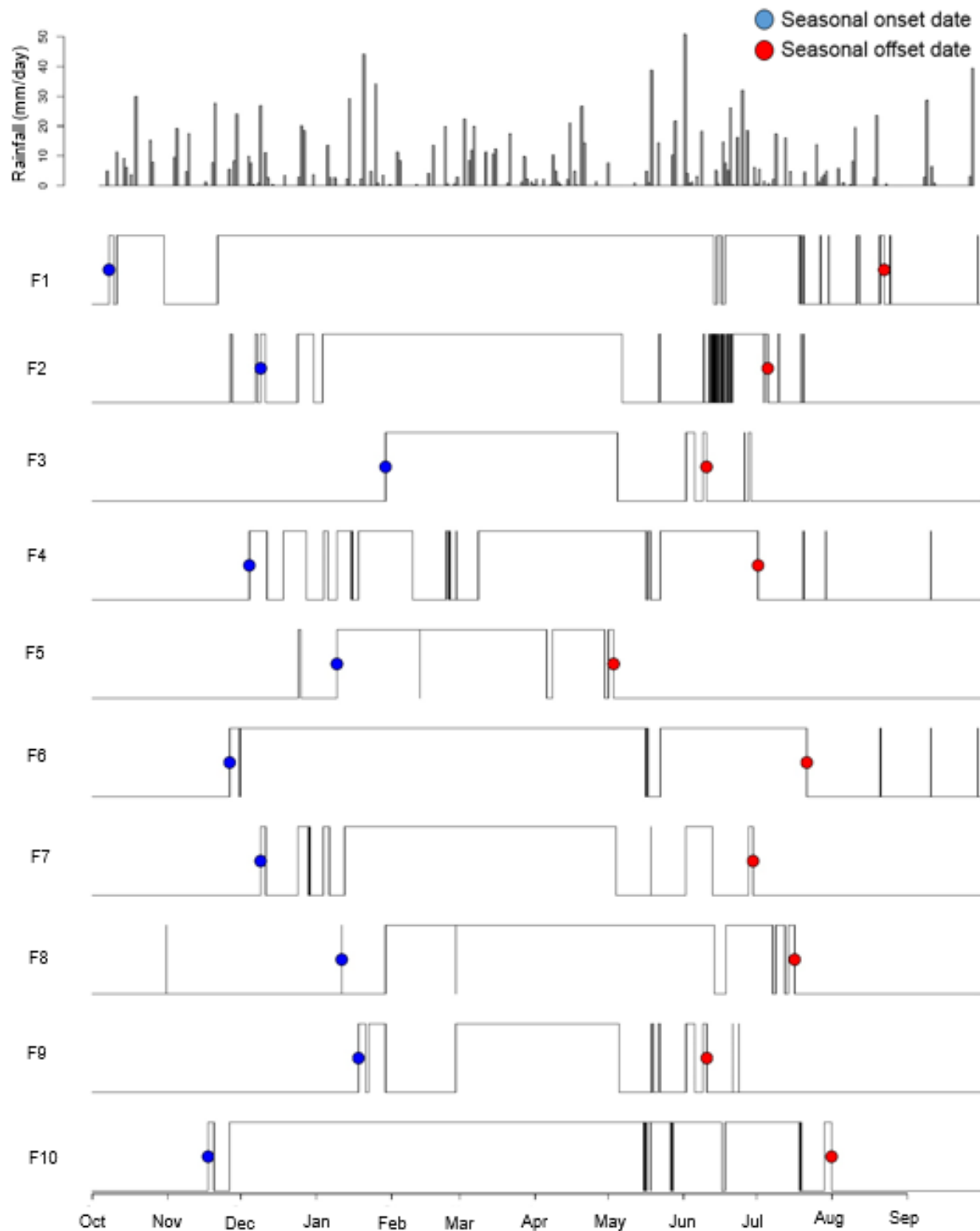
Figure 8. Daily rainfall totals (top panel) and SHC patterns for study catchments F1 to F10 during 2015 water year (1 Oct 2014 to 30 Sep 2015)
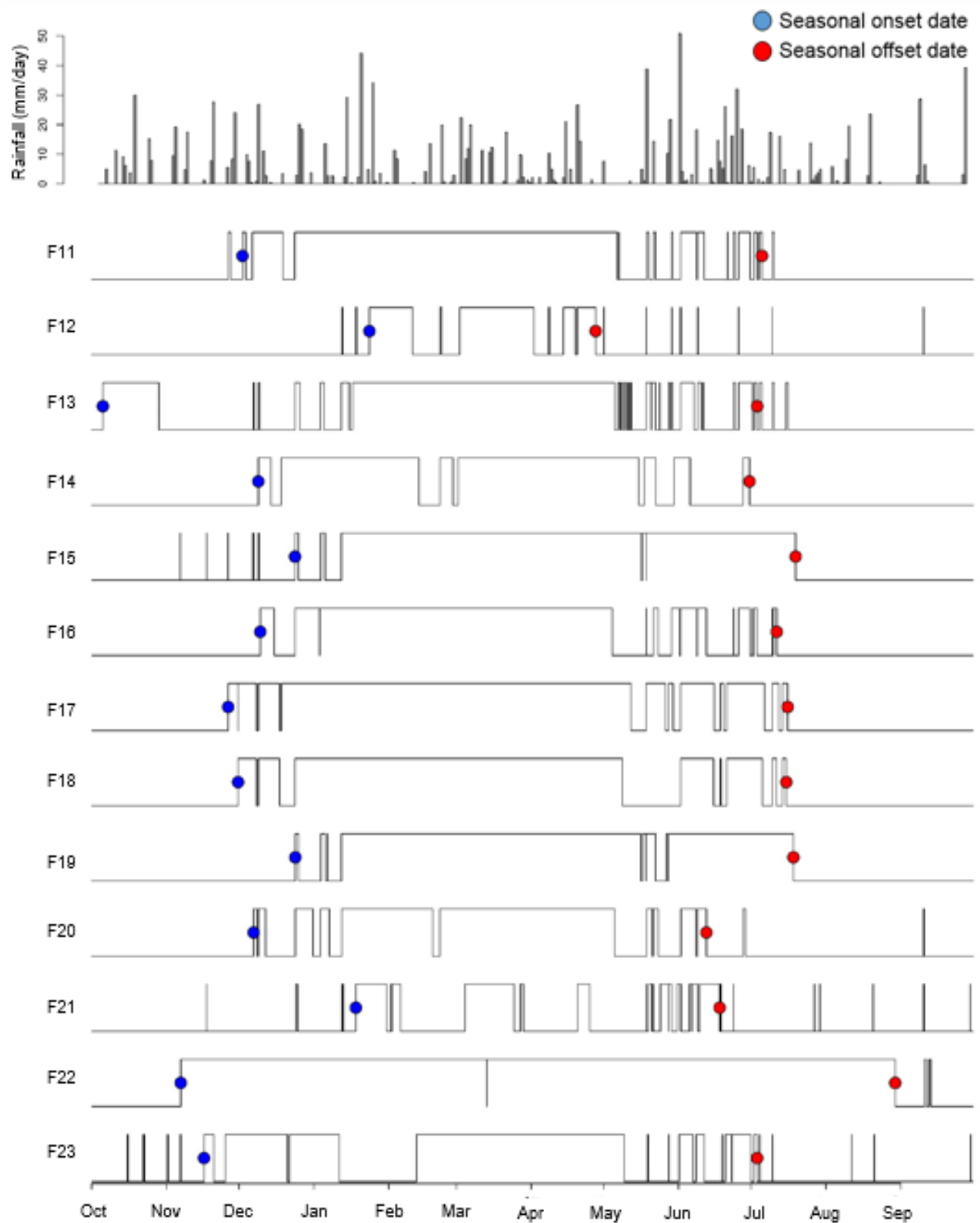
Figure 9. Daily rainfall totals (top panel) and SHC patterns for study catchments F11 to F23 during 2015 water year (1 Oct 2014 to 30 Sep 2015)

Table 2. Forested wetland-stream surface hydrologic connectivity metrics for the 2015 water year (1 Oct 2014 to 30 Sep 2015)

Connectivity Metric	Value (SE)
Mean cumulative connection duration (d)	164.5 (12.3)
Mean # connectivity transitions	13.7 (1.7)
Mean connection duration (d)	16.5 (2.5)
Max connection duration (d)	109.2 (9.6)
Median seasonal connection onset date	December 9
Median seasonal connection offset date	July 5

*SE = Standard Error

Measurable baseflow discharge in non-perennial streams was recorded between November 2014 and June 2015, during which time wetland surface water levels exceeded storage capacity, thus generating surface outflow to these streams. Observed baseflow discharge from forested wetlands ranged from 0.06 to 31.19 Ls^{-1} (0.002 to 1.1 $ft^3\ sec^{-1}$) (Table 3). Overall differences in non-perennial stream baseflow discharge among months were significant ($F_{7, 74} = 2.56$, $p = 0.04$). Peak discharge values were recorded in early spring (March/April), during which surface water levels generally reached peak expression (Lang et al. 2012) (Fig. 10).

Table 3. Water year 2015 non-perennial stream baseflow discharge measurements.
--- = site not visited, * = non-continuous surface flow present, ! = continuous surface flow present, but no measurement taken

Baseflow Discharge (L s^{-1})

Site	11/30/2014	12/18/2014	1/09/2015	1/11/2015	1/29/2015	2/12/2015	3/12/2015	3/13/2015	3/29/2015	4/16/2015	5/05/2015	6/25/2015
F1	1.09	3.73	---	0.46	---	---	---	11.44	5.55	6.43	2.11	---
F2	*	*	---	!	---	---	---	7.14	2.10	2.77	0.17	---
F3	*	*	*	---	0.11	NA	---	1.45	0.79	0.63	*	---
F4	*	!	0.19	---	2.12	---	---	7.16	7.85	3.90	0.25	---
F5	*	*	!	---	0.52	---	---	1.04	0.21	0.78	*	---
F6	0.06	3.37	2.83	---	31.19	---	---	20.78	11.98	12.19	2.61	---
F7	---	---	*	---	---	0.25	1.71	---	---	---	---	---
F8	*	*	---	!	8.33	---	12.38	---	11.44	---	4.01	---
F9	*	*	---	*	*	---	4.01	---	1.62	---	*	---
F10	---	---	---	---	1.69	0.25	1.13	---	---	---	---	---
F11	---	---	---	---	1.12	0.22	0.99	---	---	---	---	---
F12	---	---	---	---	0.39	*	0.25	---	---	---	---	---
F13	*	*	*	---	---	---	---	!	0.13	0.08	*	---
F14	---	0.06	!	---	4.43	---	---	2.00	!	---	!	*
F15	---	---	---	*	---	2.04	2.21	---	---	---	---	---
F16	---	---	---	!	---	2.53	8.82	---	---	---	---	---
F17	0.07	0.89	1.58	---	5.93	---	---	10.60	7.04	10.48	0.74	1.23
F18	*	*	0.57	---	2.58	---	---	3.87	3.26	2.43	0.18	0.20
F19	---	*	*	---	2.70	---	---	3.70	1.04	---	*	*
F20	---	*	---	---	!	---	---	1.18	*	---	*	*
F21	---	---	---	---	---	---	---	0.16	---	---	---	---
F22	---	---	---	---	---	---	---	!	---	---	---	---
F23	---	---	---	!	---	0.54	---	2.05	---	0.59	---	---
Mean	0.41	2.01	1.29	0.46	5.09	0.97	3.94	5.58	4.42	4.03	1.44	0.72
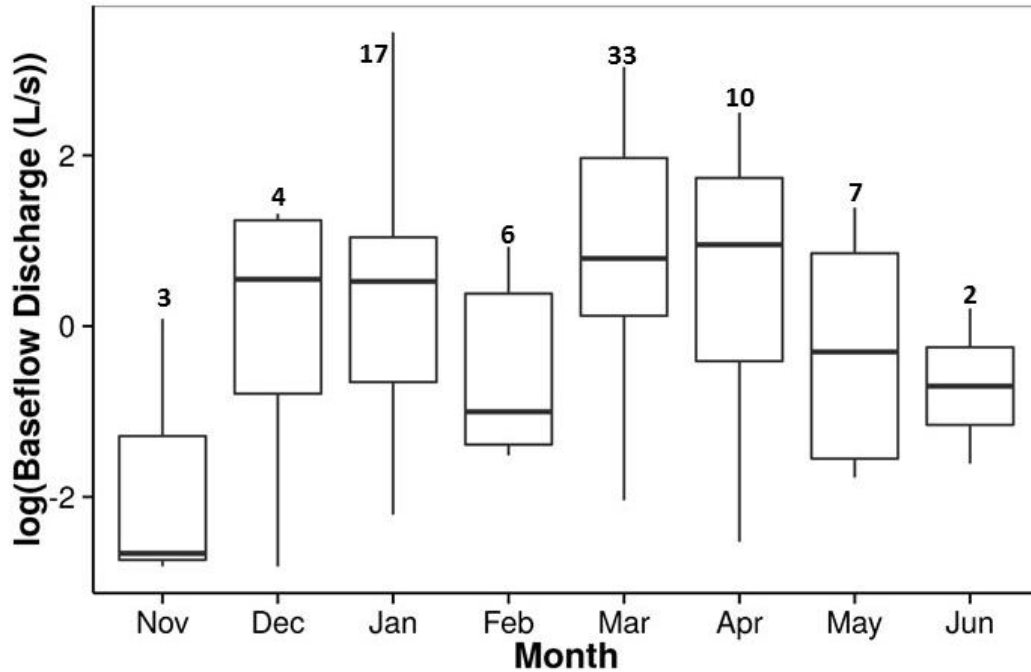
Figure 10. Boxplots of non-perennial stream baseflow discharge values (log-transformed) collected each month during water year 2015. Text above boxplots indicates number of discharge measurements collected.

Landscape metrics as predictors of SHC

Cumulative connection duration was significantly correlated with landscape metrics in all four predictor groups (10 total). The strongest correlations were with wetland and non-perennial stream metrics: *ln-wetland area* (r = 0.65, *p* < 0.01), *number wetlands* (r = 0.63, *p* < 0.01), *ln-non-perennial stream channel bankfull width* (r = 0.60, *p* < 0.01), *ln-wetland hydrologic permanence score* (r = -0.60, *p* < 0.01), and *ln-catchment area* (r = 0.55, *p* < 0.01) (Table 4).

Table 4. Pearson's product moment correlation between surface hydrologic connectivity metrics and landscape predictor metrics. Reported correlation coefficients are significant at $\alpha = 0.05$ (*) or $\alpha = 0.01$ (**) statistical levels. See Table 1 for explanation of landscape predictor metric abbreviations

Landscape predictor group	Predictor Metric	Cumulative connection duration (d)	Seasonal connection onset date	Seasonal connection offset date
Catchment	CatchArea [a]	0.55**		0.64**
	CatchSlope		0.46*	
	CatchRelief			0.53**
	HI			
	CatchOutElev			
	CatchShape			
	CatchVolStorage [a, e]			
	TWI [b]		0.52*	
	Dd [a]		-0.52*	
	Forest [g]			
Non-perennial stream	StreamRelief [c]			
	StreamLength [a, c]	0.44*	-0.42*	0.50*
	StreamSlope [c, g]			
	BFW [a, c]	0.60**	-0.49*	0.53**
	BFD [c]	0.49*	-0.43*	
	CSA [a, c]	0.54**	-0.47*	0.45*
	WD$_{ratio}$ [a, c]			
Wetlands	WetArea [a]	0.65**		0.68*
	WetRelief [a]			
	MeanWetDist [e]	-0.51*		
	MinWetDist [e]			-0.48*
	NumWet	0.63**		0.65*
	WetInunScore [a, f]	-0.60**		-0.63*
Soils	Infil$_{drained}$ [a, d]			
	Infil$_{undrained}$ [d]			
	WaterStorage [d]	0.47*	-0.44*	
	WT$_{depth}$ [d]			
	ksat [d]			

[a] ln(x) transformed

[b] 1/(x) transformed

[c] Field-derived

[d] Area-weighted mean

[e] Normalized by catchment area

[f] Normalized by wetland area

[g] Spearman rank correlation conducted due to heavily skewed predictor metric distribution
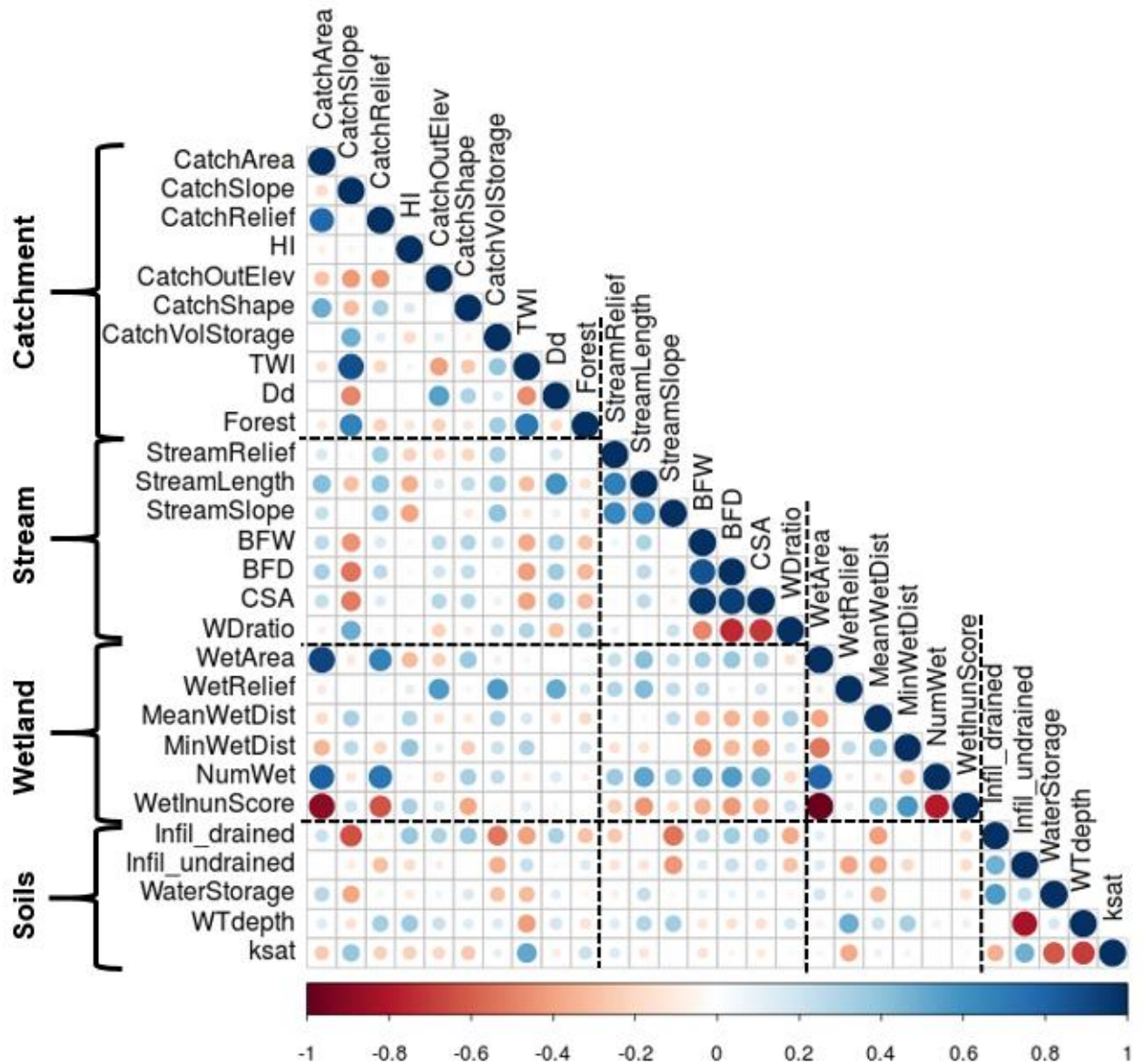
Figure 11. Correlation matrix of landscape predictor metrics, where circle color and size represent the strength and direction (positive or negative) of the correlation between each predictor metric pair. See Table 1 for explanation of landscape predictor metric abbreviations

Landscape metrics (8 total) in the catchment, non-perennial stream, and soils predictor groups were significantly correlated with seasonal connection onset date (Table 4). Strongest correlations were with catchment and non-perennial stream metrics: *inverse-median TWI value* (r = 0.52, *p* = 0.05), *ln-drainage density* (r = -0.52, *p* = 0.05), *ln-non-perennial stream bankfull width* (r = -0.49, *p* < 0.05), *ln-non-perennial stream cross-sectional area* (r = -0.47, *p* < 0.05), and *median catchment slope* (r = 0.46, *p* < 0.05).

Landscape metrics (9 total) in all four predictor groups were significantly correlated with seasonal connection offset date (Table 4). The following predictor metrics were most strongly correlated with prolonged (>24 hour) SHC events that occurred later in the 2015 water year: *ln-wetland area* (r = 0.68, *p* < 0.05), *number wetlands* (r = 0.65, *p* < 0.05), *ln-catchment area* (r = 0.64, *p* < 0.01), *ln-wetland hydrologic permanence score* (r = -0.63, *p* < 0.05) (Table 4).

Three non-perennial stream metrics were significantly correlated with all three SHC metrics: *non-perennial stream length*, *non-perennial stream bankfull width*, and *non-perennial stream cross-sectional area* (Table 4). Longer, deeper channels were associated with more prolonged periods of surface flow that initiated earlier and remained longer through the water year.

Models built as a function of both field and GIS-derived predictor metrics explained the most variability in cumulative connection duration (Adj. R^2 = 0.80), followed by seasonal connection onset date (Adj. R^2 = 0.69) and seasonal connection offset date (Adj. R^2 = 0.53) (Table 5). However, the AICc results indicated that model accuracy was not significantly improved by the addition of field-derived predictors. For

each SHC metric, the removal of field-derived predictor metrics from stepwise regression resulted in final GIS-based models with ΔAICc values of -4.0 (connection duration), -0.2 (seasonal connection onset date), and 2.1 (seasonal connection offset date) (Table 5). Models with a ΔAICc value greater than three are generally considered to have considerably less support than the minimum AICc model for a given dataset (Burnham and Anderson 2002). Using this threshold suggests no need to retain field-derived predictor metrics in the models. The asymptotic z-test comparing the correlation coefficients of observed vs. predicted values between the GIS+Field and GIS-based corroborated this result, as indicated by nonsignificant differences in the observed vs. predicted correlation strengths.

Table 5. Comparison of stepwise regression models developed for each SHC metric using (1) GIS-based predictor metrics, and (2) field and GIS-based predictor metrics. Models built using full dataset (n = 23). See Table 1 for full predictor metric names and descriptions

Response Variable	Predictor groups used in model	Final Model	Model AICc Value	Model Adjusted R^2 Value	Model Observed vs. Predicted Values
Cumulative SHC duration (days)	Field and GIS	= -190.6 – 31.3 (CatchShape) + 10.7 (Dd) + 79.6 (Forest) + 61.9 (BFW) + 15.0 (WetArea) + 3.0 (NumWet) + 13.3 (WaterStorage)	237.5	0.80, $p < 0.0001$	r = 0.92, $p < 0.0001$
	GIS	= -260.5 + 42.4 (WetArea) + 11.1 (NumWet) + 21.0 (WaterStorage) – 51.2 (CatchArea)	233.5	0.74, $p < 0.0001$	r = 0.89, $p < 0.0001$
Connection onset date (Julian date)	Field and GIS	= -267.7 – 11.6 (CatchArea) + 44.5 (CatchShape) + 79.6 (TWI) – 14.6 (Dd) – 77.3 (Forest) – 22.6 (BFW) + 16.0 (WetRelief)	218.0	0.69, $p = 0.0004$	r = 0.89, $p < 0.0001$
	GIS	= -272.7 + 24.1 (CatchShape) + 99.3 (TWI) – 76.3 (Forest) – 2.9 (NumWet) – 4.0 (WaterStorage)	217.8	0.58, $p = 0.001$	r = 0.82, $p < 0.0001$
Connection offset date (Julian date)	Field and GIS	= 244.5 + 24.0 (BFW) + 12.9 (WetArea)	209.1	0.53, $p = 0.0002$	r = 0.76, $p < 0.0001$
	GIS	= 255.7 + 15.4 (WetArea)	211.3	0.44, $p = 0.0004$	r = 0.68, $p = 0.0004$

DISCUSSION

Using a field-validated, landscape-scale approach to quantify Delmarva bay wetland-stream hydrologic connectivity, this study demonstrates that field and GIS-derived predictor metrics can be used to explain and predict variability in wetland-stream connectivity at the landscape scale. By modeling connectivity metrics as a function of catchment, wetland, non-perennial stream, and soil characteristics representing likely SHC drivers, these results contribute to the new field of research aimed at developing relatively low-cost, scalable approaches for quantifying flow permanence throughout stream networks (e.g., Turner and Richter 2011, Bhamjee et al. 2015) and wetland landscapes. Combining rainfall data with continuous measurements of surface hydrologic connectivity between wetlands and non-perennial streams, this study provides evidence of changes in the underlying drivers of strong seasonal patterns in connectivity. The combination of GIS data and extensive field data from 23 wetland-stream sites allows us to narrow the suite of landscape factors influencing these drivers as well as the timing and magnitude of connectivity. An important next step is to field-test the predictions of the connectivity model developed in this study and, as in Golden et al. (2016), scale-up such studies to understand the cumulative effect of wetlands on broader waterways.

Temporal variability in wetland-stream connectivity patterns

Delmarva bays are complex systems whose degree of landscape connectivity is a function of both local and regional hydrological processes and like other depressional wetlands surface hydrologic connectivity with streams is a function of water balance within wetland catchments and landscape attributes including soils and perhaps by size (Snodgrass 2000, Leibowitz and Nadeau 2003, Sharitz 2003, Golden et al. 2016).

Connections are most likely to occur during periods when water inputs (precipitation, groundwater discharge) exceed water losses (evapotranspiration, groundwater recharge) (Lide et al. 1995, Sharitz 2003), leading to surface outflow from wetlands into nearby streams. The results from this 2015 field study indicate that, as was the case in the 2010 water year in this watershed (McDonough et al. 2014), seasonal groundwater dynamics drive the timing of prolonged ($\geq$ 24 hour) surface water connections between forested Delmarva bay wetlands and perennial streams from late-fall to late-spring. During the 2015 water year, more than half of wetland-stream surface connections turned "on" and "off" within a three-week period (Fig. 8, 9). The spatiotemporal homogeneity of SHC onset and offset dates and absence of spatial autocorrelation across the study area suggests that a seasonal drop in evapotranspiration, followed by a regional rise in groundwater table, exert first-order controls over sustained outflow of surface water ponding within bays to non-perennial streams when the water table is at or above the surface (Lide et al. 1995).

Conversely, the shortened (minutes to hours) duration of SHC events observed between late-spring and late-fall during the 2015 water year reflects a seasonal shift in the driver of SHC. These shortened SHC events coincided with the seasonal peaks in vegetation, during which Delmarva bays typically lack surface water (Phillips and Shedlock 1993, Fisher et al. 2010), and generally represented ephemeral surface water levels in non-perennial streams following rain events. Over the study year, recent rainfall amounts, as indicated by 5-day antecedent rainfall totals, were significantly higher on days when a SHC occurred compared to non-SHC days, indicating that antecedent

conditions and local fill-spill dynamics also influence wetland-stream connectivity in Delmarva bays.

The delay from SHC onset to measureable baseflow discharge in non-perennial streams suggests a mechanistic shift in the SHC driver from groundwater to surface water outflow (i.e., wetland spillage) during the winter. While the median seasonal onset date occurred on December 9, baseflow discharge was not measureable (i.e., water depth ≤ 3 cm and/or no measureable water velocity in channel) in most catchments until late-January (Table 3). Field observations confirm that this shift was aligned with bay ponding levels exceeding their relative spill thresholds and flowing into the adjacent non-perennial streams (Fig. 6). This finding is consistent with the model of wetland connectivity described by Winter and LaBaugh (2003), in which surface outflow is described as a function of groundwater flow, spill elevation above normal wetland water level, and the timing of precipitation events.

The effects of seasonal shifts in surface and groundwater dynamics on hydrology at the landscape scale are evident in baseflow discharge in Tuckahoe Creek, a tributary to the Choptank River, between December and July (Fig. 12), suggesting the wetlands contribute to stream surface flows at least some time of the year. Surface water levels in the Coastal Plain physiographic province generally reach peak expression in early spring (Lang et al. 2012), which coincided with peak observed non-perennial stream baseflow discharge values during the 2015 water year. Additionally, it is well-documented that depressional wetlands, in aggregate, have a substantial effect on watershed-scale water balances by increasing seasonally-defined subsurface storage and groundwater flow (Evenson et al. 2015). In their analysis of the spatially based statistical relationships

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between geographically isolated wetland characteristics and streamflow in the Middle

Atlantic Coastal Plain ecoregion (North Carolina, U.S.), Golden et al. (2016) report that

wetlands exhibited a flow attenuation capacity across seasons and annually. They also

report a seasonal effect on the relationship between wetland characteristics and

streamflow, including a significant relationship between depressional swamp forest

geographically isolated wetland area and streamflow during the spring, when poorly

drained wetland systems respond rapidly to precipitation events (Golden et al. 2016).

Regressions in the current study indicated that one or both of the wetland area and

wetland number metrics was related to connection duration and seasonal offset date

(Table 5). Future studies are needed to quantify the partitioned (surface water vs.

groundwater) and/or aggregate effect of wetland-stream connectivity on downstream

waters (e.g., mean seasonal increase in mainstem river baseflow during connections). In

addition to linking SHC patterns to downstream ecological processes, future studies

should investigate the relationship between wetland-stream groundwater hydrologic

connectivity and landscape characteristics (e.g., bay size, soil type; McLaughlin et al.

2014) to better quantify the downstream effects of such connections.
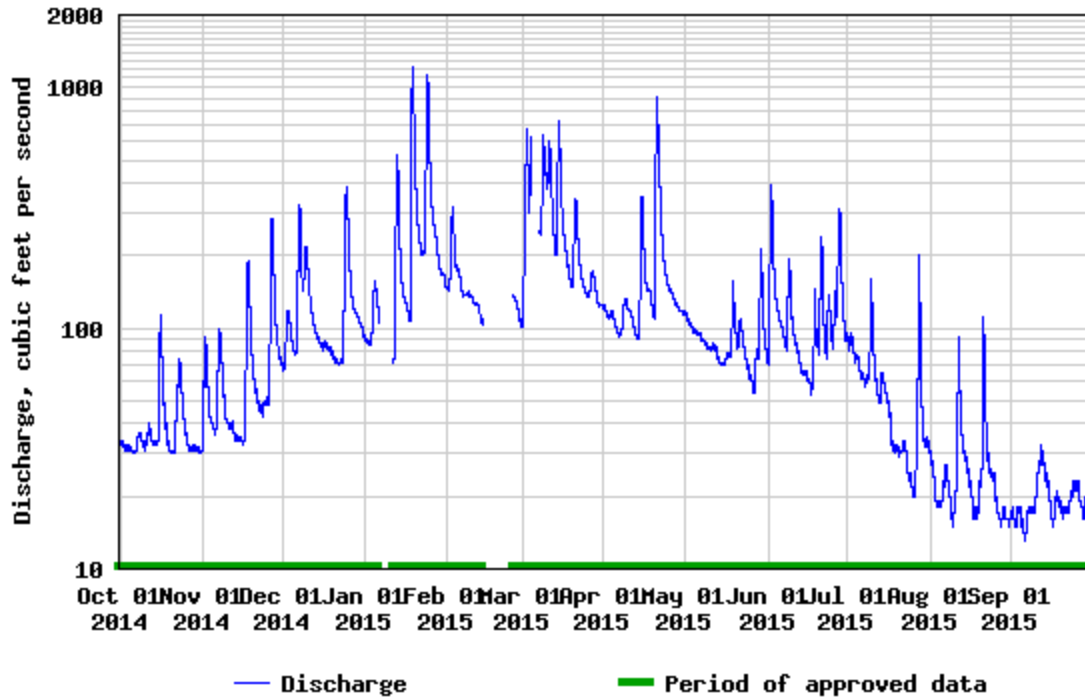
Figure 12. Stream discharge (cfs) record for Tuckahoe Creek near Ruthsburg, MD (USGS station 01491500) for the 2015 water year. Data and graphic acquired from the USGS WaterWatch web portal (accessed 08 Jan 2016)

Landscape characteristics as predictors of wetland-stream connectivity patterns

Among the landscape predictor metrics, non-perennial stream length, bankfull width, and cross-sectional area were significantly correlated with all three SHC metrics, and bankfull width was a significant predictor in all final regression models. Bankfull channel measurements refer to the physical dimensions of streams that transmit flows that may influence the formation and maintenance of channels (Wolman and Miller 1960). Several studies have reported these physical measurements to be significant predictors of stream flow duration, including bankfull width (Svec et al. 2005, Fritz et al. 2013) and entrenchment ratio (flood prone width divided by bankfull width; Svec et al. 2005, Fritz et al. 2008), though Fritz et al. (2013) caution they may be weak predictors in high rainfall, low topographic relief regions with low erosive potential.

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While correlations between metrics do not imply causation, I propose two mechanisms that may explain the observed relationships between SHC metrics and non-perennial stream channel geomorphology. Given the shallow regional depth to groundwater in the Coastal Plain (minimum recorded depth at a nearby well during the 2015 water year was 0.86 m; USGS well, ID 390839075515001 QA Cg 69; 39°08′39.8″N, 75°51′50.8″W), surface water presence in non-perennial stream channels may be an expression of groundwater (Winter 1988). As a result, larger (i.e., deeper, wider) non-perennial stream channels may experience more prolonged flow duration (or at a minimum, water presence), including during periods before and after wetland-stream SHC. Secondly, larger stream channels may be evidence of the effect of higher flows from wetland surface outflow on maintaining or actively shaping channels. In their study of flow duration in headwater streams throughout South Carolina Piedmont and Southeastern Plains, where catchment relief and stream discharge values were similar to this study, Fritz et al. (2013) cite channel geomorphology as an important parameter in discriminating headwater stream flow class.

In general, larger, wetter (greater number and area of wetlands, higher wetland hydrologic permanence score) catchments were associated with greater cumulative SHC duration and later SHC offset dates. These results agree with earlier findings that wetland area (McDonough et al. 2014) and total catchment area (Lampo 2014) are positively related to headwater stream flow duration in flat, well-drained landscapes. Larger, wetter catchments were also associated with larger non-perennial stream channels, illustrating the potential effect of collinearity among landscape predictor metrics in masking alternative drivers of observed SHC patterns (Fig. 11). For example, close linkages

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between catchment topography, wetlands, non-perennial stream geomorphology, and soils could explain individual relationships between landscape predictor metrics and SHC metrics. More prolonged surface water ponding in deeper stream channels as a result of exposed, shallow groundwater table or more extensive historical ditching of wetter catchments resulting in greater surface drainage of bays today are two of several examples of how multiple, related factors influence catchment hydrology. These complex relationships present challenges in isolating single drivers of SHC. Future studies should consider paired-sensor approaches to discriminate between periods of ponding (i.e., groundwater-fed) and streamflow (i.e., wetland surface outflow) in non-perennial streams connecting wetlands and streams (Bhamjee et al. 2015), which may help better link landscape characteristics to hydrological patterns.

The relationships between landscape characteristics and catchment hydrological patterns described in this study can help explain land use patterns and hydrology at the broader watershed scale. For example, spatial variation in soils and topography is inextricably linked to land use history and hydrology within the Choptank River watershed. Today, the amount of remaining forested area (26%) is consistent with the proportion of hydric, poorly drained soils (27%) within the watershed (Lee et al. 2000). During intensive deforestation in the 1700 and 1800's, forests remained primarily in poorly drained stream corridors too wet for agriculture (Fisher et al. 2006). High relief and good drainage has resulted in high farmland:forest land cover ratio in the well-drained uplands hydrogeomorphic region of the watershed. Conversely, larger amounts of forested wetlands are found in low topographic gradient areas within the poorly drained uplands region (Phillips et al. 1993) (Fig. 13). Deeper non-perennial stream channels

within larger, wetter catchments observed in this study may be explained in part by

historical efforts to more effectively drain these wetter areas.
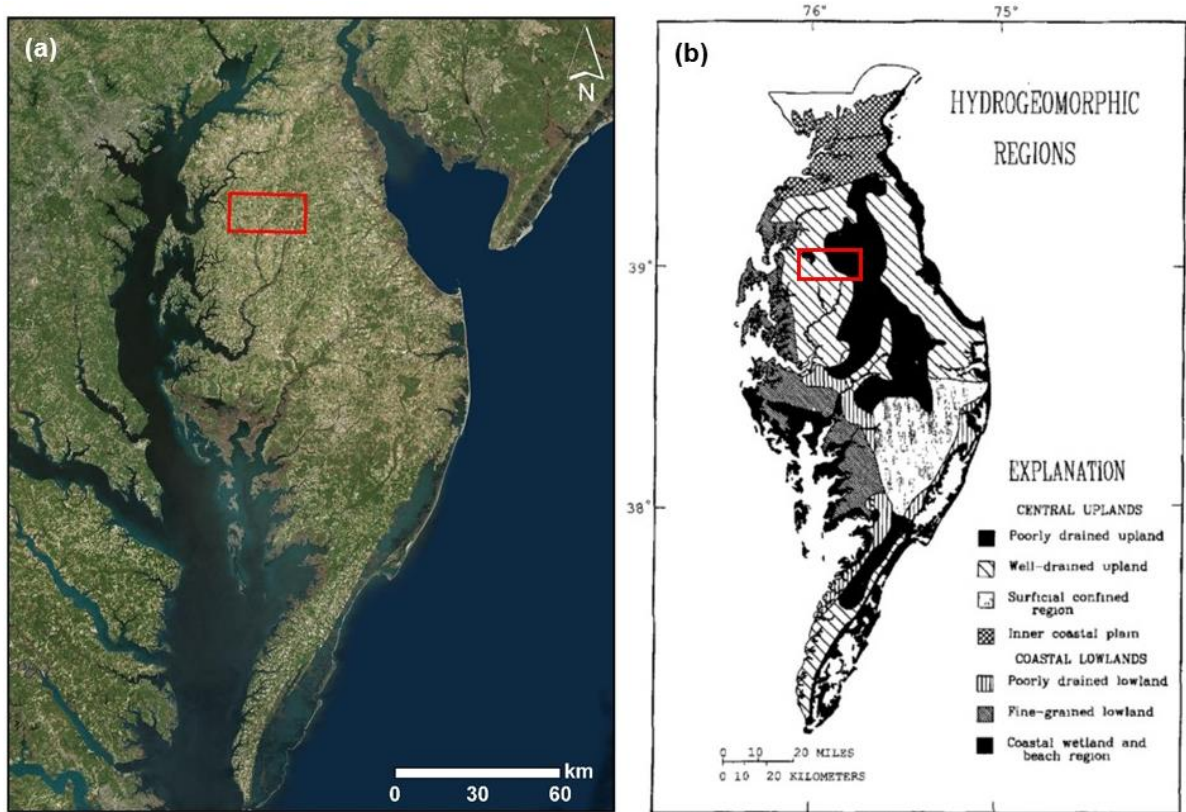
Figure 13. Delmarva Peninsula aerial imagery (ESRI; Redlands, CA) (a) and hydrogeomorphic regions (b). Red box indicates study area. Figure (b) from Phillips et al. (1993); reprinted with kind permission from Springer Science and Business Media

In addition to the effects on land use, soil drainage properties and topography

have been cited as important drivers of hydrology within the Choptank River watershed.

Koskelo (2008) reports that stream baseflow discharge is inversely related to areal

percentage hydric soils, due to larger evaporative losses along the surface and shallow

subsurface, resulting in decreased groundwater recharge. McLaughlin et al. (2014)

integrated models of soil moisture, upland water table, and wetland stage to simulate the

hydrology of a low-relief landscape with GIWs. Their models suggest that increasing

total wetland area and decreasing individual wetland size substantially decreases water

table and base flow variation; this is attributed to the cumulative effect that local sink/source reversal of small GIWs can have in buffering surficial aquifer and base flow dynamics (referred to as "hydrologic capacitance") (McLaughlin et al. 2014). Within the present study, the lack of significant correlations between soil-based predictor metrics and SHC values may be reflective of the coarse SSURGO dataset spatial scale (minimum mapping unit of 0.6 ha) relative to forested wetland catchment areas, which ranged from one to 71.2 ha. Future studies should investigate the use of higher quality soils datasets to explore the relationship between soil type, and surface/ground water connectivity dynamics.

Evaluating the accuracy of landscape predictor-based regression models

Stepwise regression has been applied in several other studies within the mid-Atlantic Coastal Plain region of the U.S. to model hydrological patterns as a function of landscape characteristics (e.g., Julian et al. 2012, McDonough et al. 2014). Applying a similar technique in this study provides an opportunity to compare findings. Based on final model AICc values and nonsignificant differences in observed vs. predicted correlation strengths between GIS+Field and GIS-based models, the addition of field-derived predictor metrics did significantly improve model performance (Table 5). In fact, the removal of field-derived predictor metrics from stepwise regression led to a final GIS-based model of cumulative SHC duration with considerably *more* support, as indicated by a decrease in AICc value of 4.2 (Burnham and Anderson 2002). These results suggest that among the variables used in this study, GIS+Field and GIS-based models performed comparably in their ability to explain variability in SHC patterns among forested Delmarva bay wetland catchments.

These results support other recent findings that improvements in the quality and spatial resolution of remote sensing and GIS products provide increasing opportunities to accurately model hydrological patterns as a function of GIS-based variables. In their study linking landscape attributes to channel head locations, Julian et al. (2012) concluded that the occurrence of channel heads across Maryland's Coastal Plain was most likely driven by saturation overland flow given the sandy soils and close proximity of the water table. Further, they note that sorted bedload and definable banks were often evident several meters downstream of wetlands. Results from the present study support their findings, as GIS-based indicators of contributing area (CatchArea), wetland extent (WetArea, NumWet), and saturation overland flow potential (WaterStorage) were included in final models of surface flow duration and seasonal connection onset date in headwater streams. Contributing area, which can be readily calculated using DEM analysis techniques, has been consistently reported as a significant predictor of flow permanence in a range of geographic settings (Montgomery and Dietrich 1988, Bent and Steeves 2006, Fritz et al. 2013).

However, results from the present study also demonstrate the value of field-based measurements in representing drivers of SHC in forested Delmarva bay systems. As described above, the density and physical dimensions of channels is closely linked to the degree of historical efforts to drain wet areas on the landscape. The addition of field-derived metrics in stepwise regressions resulted in final models that included drainage density and non-perennial stream bankfull width as significant predictors of cumulative SHC duration and seasonal onset date (Table 5). Though not significant, two interesting relationships emerged when comparing the differences in mean drainage densities

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between (a) catchments for which the GIS-based model predicted earlier vs. later connection onset dates than observed, and (b) catchments for which GIS-based models overestimated vs. underestimated all measures of SHC. The mean drainage density among catchments for which the GIS-based model predicted earlier connection onset date than observed was nearly significantly less compared to the mean drainage density among catchments for which the model predicted later connection onset date than observed. In other words, catchments with greater non-perennial stream channel extent were more likely to have predicted seasonal onset dates later in the water year than those observed during the 2015 water year. As reported in Table 5, drainage density had a significant negative correlation ($r = -0.52$, $p < 0.05$) with seasonal connection onset date. In excluding the field-derived drainage density measurement, the GIS-based model failed to accurately predict the onsets of seasonal SHC connections in catchments with more extensive historical ditching and natural surface flowpaths.

Conversely, the mean drainage density among catchments for which GIS-based models overestimated all measures of SHC (earlier onset dates, later offset dates, longer SHC duration) was nearly significantly greater compared to catchments for which models underestimated all measures of SHC (Fig. 14). Given the variable strength and direction of the relationships between ln-drainage density and the SHC metrics (Fig. 15), it is evident that SHC patterns are driven by a complex set of hydrologic drivers, many of which were not represented in the predictor metrics developed in this study. For example, higher drainage densities likely have different implications on hydrological patterns when representing increased stream channel extent through different hydrogeomorphic (HGM) wetland classes. Future studies should explore GIS-based techniques to more accurately

determine the spatial extent of channelization through forest wetlands, a particular

challenge in a low-relief setting (Lang et al. 2012).
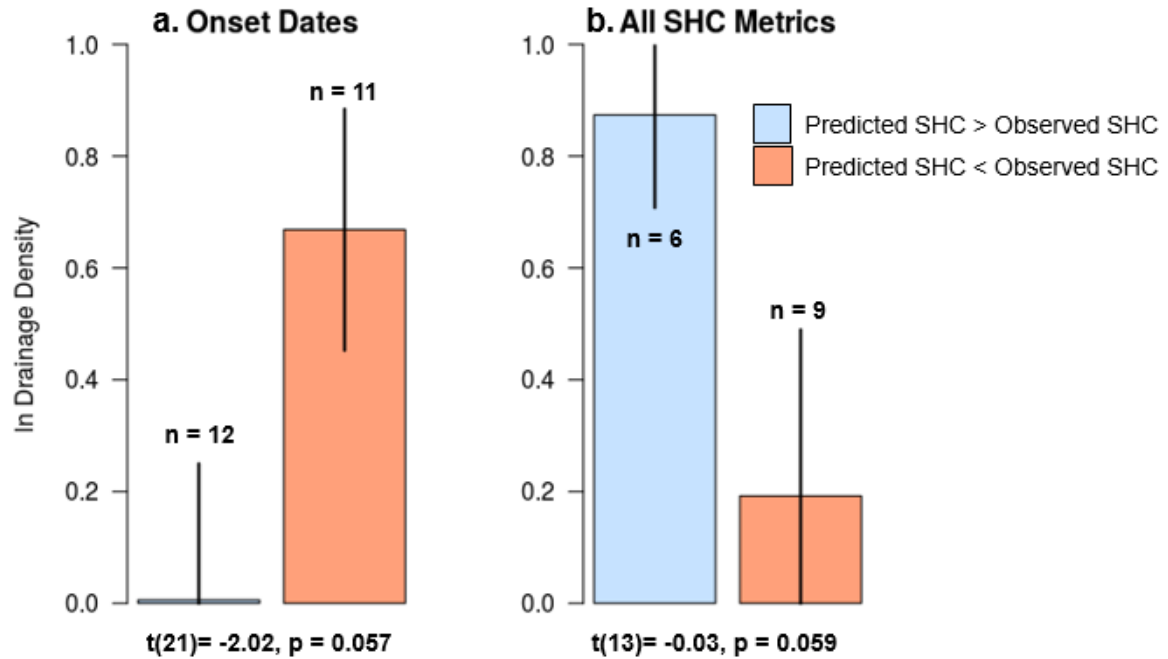
Figure 14. Two-sample t-test results comparing mean ln-drainage density among (a) catchments for which the GIS-based model predicted earlier (blue) vs. later (orange) onset SHC dates than observed, and (b) catchments for which GIS-based models overestimated (earlier onset dates, later offset dates, longer SHC duration; blue) vs. underestimated (later onset dates, earlier offset dates, shorter SHC duration; red) all measures of SHC. Error bars are standard errors of the means
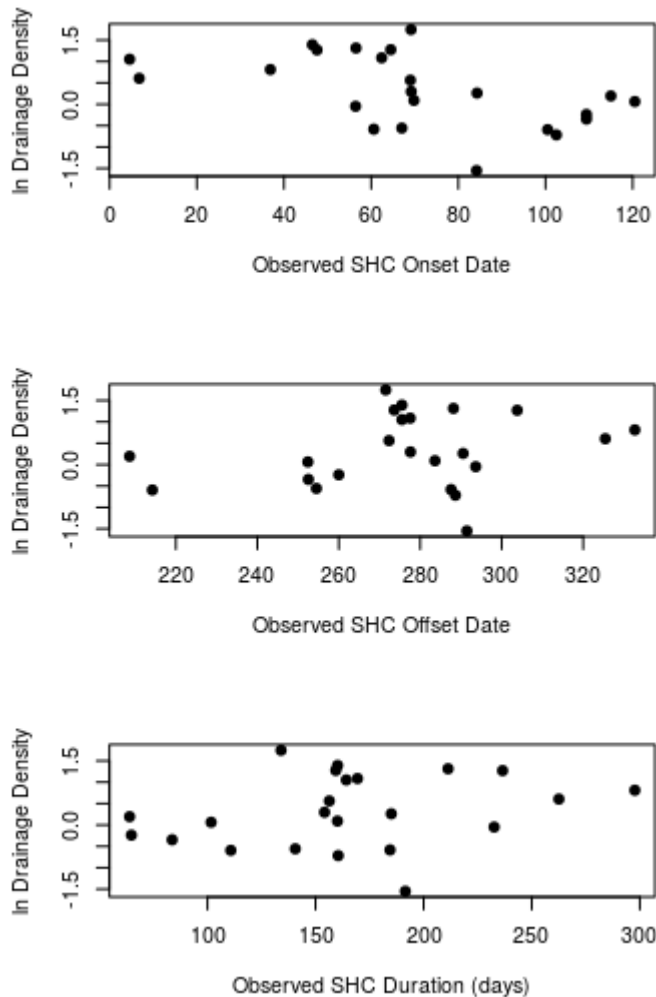
Figure 15. Relationships between ln-drainage density and observed SHC onset dates, offset dates, and cumulative connection duration (n = 23). The only significant correlation is between ln-drainage density and SHC onset date (r = -0.52, p < 0.05)

A potential framework for assessing connectivity at the watershed scale

Following key U.S. Supreme Court rulings and the subsequent implementation of "significant nexus" tests over the last several years to assess the jurisdictional status of case-specific waters across the United States, the Clean Water Rule (USEPA and USACE 2015) attempts to minimize the need for case-specific analyses for CWA jurisdictional determination. Despite these clarifications, the rule retains the need for case-specific "significant nexus" analyses to assess the jurisdictional status of some groups of waters,

including Delmarva bays (Alexander 2015). In cases when the significant nexus

argument is invoked, the implementing agencies will consider a range of specific

functions to assess the extent to which a water affects the chemical, physical, or

biological integrity of known jurisdictional waters. These functions include "sediment

trapping; nutrient cycling; pollutant trapping, transformation, filtering, and transport;

retention and attenuation of floodwaters; runoff storage; contribution of flow; export of

organic matter; export of food resources; and provision of life-cycle dependent aquatic

habitat (such as foraging, feeding, nesting, breeding, spawning, and use as a nursery area)

for species located in traditional navigable waters, interstate waters, or the territorial

seas" (USEPA and USACE 2015). Delmarva bays provide a number of functions on the

landscape, which are in part influenced by their degree of surface hydrologic connectivity

with surrounding waters (Leibowitz et al. 2008, McDonough et al. 2014). Through the

development of empirically-based models, the present study demonstrates that variability

in SHC patterns between forested wetlands and nearby perennial waters can be explained

as a function of both GIS and field-derived landscape predictor metrics.

To my knowledge, this is one of only two studies (McDonough et al. 2014) that

provides a robust, field-based dataset on the SHC patterns between forested Delmarva

bay wetlands and perennial streams. As such, this study addresses the need for research

on the frequency, magnitude, timing, and duration from GIWs to downgradient waters

(Rains et al. 2016). Moving forward, studies should focus on linking observed and

modeled wetland-stream connectivity patterns to ecological data. For example, Fellman

et al. (2009) report that flows during fall storm events are responsible for a substantial

proportion of biodegradable dissolved organic carbon transport in forested wetland-

dominated watersheds. Preliminary data from long-term dissolved organic matter (DOM) sensors in the present study area suggest there are seasonal trends in DOM transport from forested wetland catchments linked to rainfall. Linking predicted wetland-stream SHC to downstream hydrological (e.g., discharge) and ecological (e.g., DOM) data will provide valuable insights on the relative and total importance of surface and subsurface flow in establishing functional connections between wetlands and streams. In developing models that more accurately depict the spatial extent and flow permanence of stream networks, this study provides a critical first step in linking hydrological patterns to ecological data, which will ultimately influence the jurisdictional status of many surface waters, including geographically isolated wetlands, across the United States (Alexander 2015).

CONCLUSION

Linking SHC patterns to landscape structure provides an important foundation for understanding drivers of connectivity. Correlations between SHC metrics and landscape characteristics indicate the integrated effect of topography, soils, and land use history on catchment hydrology. Among landscape predictor metrics, variability in SHC metrics was most strongly explained by *catchment area*; *wetland area*, *number*, and *mean wetland hydrologic permanence score*; and *non-perennial stream channel dimensions*. Larger, wetter catchments with deeper non-perennial stream channels were associated with greater cumulative SHC duration and later seasonal connection offset dates. The lack of significant differences in model accuracy, as determined by assessing differences in model AICc values and observed vs. predicted correlations strengths, indicates that among the variables used in this study, the addition of field-derived predictor metrics did

not significantly improve model performance. Results from this study may be applicable for assessments of forested Delmarva and Carolina bays across the U.S. Mid-Atlantic and Southeastern Coastal Plain, where climate and hydrological inputs and losses are expected to be similar to the study area. Future studies can build on these efforts by collecting empirical measurements of wetland-stream connectivity (e.g., by deploying larger sets of surface flow loggers in stream networks), then assessing the predictive ability of landscape predictor metrics and models presented in this study. These predictions may be paired with temporal datasets (e.g., stream discharge, DOM flux) to assess the effects of connectivity on downstream ecologic processes.

Literature Cited

Adler RW (2015) US Environmental Protection Agency's new Waters of the United States Rule: connecting law and science. *Freshwater Science* 34(4): 1595–1600.

Alexander LC (2015) Science at the boundaries: scientific support for the Clean Water Rule. *Freshwater Science* 34(4): 1588–1594.

Ali G, Tetzlaff D, McDonnell JJ, Soulsby C, Carey S, Laudon H, McGuire K, Buttle J, Seibert J, Shanley J (2015) Comparison of threshold hydrologic response across northern catchments. *Hydrological Processes* 29(16): 3575-3591.

Ator, S., J. Denver, D. Krantz, W. Newell, S. Martucci (2005) A surficial hydrogeologic framework for the Mid-Atlantic Coastal Plain. U.S. Geological Survey professional paper 1680.

Austin PC, Steyerberg EW (2015) The number of subjects per variable required in linear regression analysis. *Journal of Clinical Epidemiology* 68: 627-636.

Bartzen BA, Dufour KW, Clark RG, Caswell FD (2010) Trends in agricultural impact and recovery of wetlands in prairie Canada. *Ecological Applications* 20(2): 525-538.

Benke AC (1990) A perspective on America's vanishing streams. *Journal of the North American Benthological Society* 9(1): 77–88.

Bent GC, Steeves PA (2006) A revised logistic regression equation and an automated procedure for mapping the probability of a stream flowing perennially in Massachusetts. US Department of the Interior, US Geological Survey.

Beven K, Kirkby M (1979) A physically-based, variable contributing area model of basin hydrology. *Hydrol. Sci. Bull.* 24, 43-69.

Beyer HL (2012) Geospatial Modelling Environment (Version 0.7.3.0). (software). URL: http://www.spatialecology.com/gme.

Bhamjee R, Lindsay JB, Cockburn J (2015) Monitoring ephemeral headwater streams: a paired-sensor approach. *Hydrological Processes*.

Blann, KL, Anderson JL, Sands GR, Vondracek B (2009). Effects of agricultural drainage on aquatic ecosystems: a review. *Critical reviews in environmental science and technology* 39(11): 909-1001.

Bracken LJ, Croke J (2007) The concept of hydrological connectivity and its contribution to understanding runoff-dominated geomorphic systems. *Hydrological Processes* 21: 1749–1763.

Burnham KP, Anderson DR (2002) Model selection and multimodel inference: a practical information- theoretic approach. 2nd edition. Springer, New York.

Cook BJ, Hauer FR (2007) Effects of hydrologic connectivity on water chemistry, soils, and vegetation structure and function in an intermontane depressional wetland landscape. *Wetlands* 27(3): 719–738.

Cowardin LM, Carter V, Golet F, LaRoe E (1979) Classification of wetlands and deepwater habitats of the United States. U.S. Fish and Wildlife Service, Washington, DC. FWS/OBS-79/31

Daly C, Halbleib M, Smith JI, Gibson WP, Doggett MK, Taylor GH, Curtis J, Pasteris PP (2008) Physiographically sensitive mapping of climatological temperature and precipitation across the conterminous United States. *International Journal of Climatology* 28: 2031–2064.

Euliss NH, LaBaugh JW, Fredrickson LH, Mushet DM, Laubhan MK (2004) The wetland continuum: a conceptual framework for interpreting biological studies. *Wetlands* 24(2): 448–458.

Evenson GR, Golden HE, Lane CR, D'Amico E (2015) Geographically isolated wetlands and watershed hydrology: a modified model analysis. *Journal of Hydrology* 529: 240–256.

Federal Geographic Data Committee (1998) Geospatial positioning accuracy standards: part 3: national standard for spatial data accuracy. Available via https://www.fgdc.gov/standards/projects/FGDC-standards-projects/accuracy/part3/chapter3. Accessed 29 Nov 2015.

Fellman JB, Hood E, Edwards RT, D'Amore DV (2009) Changes in the concentration, biodegradability, and fluorescent properties of dissolved organic matter during stormflows in coastal temperate watersheds. *Journal of Geophysical Research* 114: 1–14.

Fenstermacher DE, Rabenhorst MC, Lang MW, McCarty GW, Needelman BA (2014) Distribution, morphometry, and land use of Delmarva bays. *Wetlands* 34: 1219–1228.

Fisher TR, Benitez JA, Lee K-Y, Sutton AJ (2006) History of land cover change and biogeochemical impacts in the Choptank River basin in the mid-Atlantic region of the US. *International Journal of Remote Sensing* 27(17): 3683–3703.

Fisher TR, Jordan TE, Staver KW, Gustafson AB, Koskelo AI, Fox RJ, Sutton AJ, Kana T, Beckert KA, Stone JP, McCarty G, Lang MW (2010) The Choptank basin in transition: intensifying agriculture, slow urbanization, and estuarine eutrophication.

In: MJ Kennish and HW Paerl (eds) Coastal Lagoons: Systems of Natural and Anthropogenic Change. CRC Press, pp 135–165

Fritz KM, Johnson BR, Walters DM (2008) Physical indicators of hydrologic permanence in forested headwater streams. *Journal of the North American Benthological Society* 27: 690–704.

Fritz, KM, Johnson BR, Walters DM (2006) Field operations manual for assessing the hydrologic permanence and ecological condition of headwater streams. EPA 600/R-06/126 USEPA Office of Research and Development, National Exposure Research Laboratory, Cincinnati, Ohio.

Fritz KM, Johnson BR, Walters DM (2008) Physical indicators of hydrologic permanence in forested headwater streams. *Journal of the North American Benthological Society* 27: 690–704.

Fritz KM, Wenerick WR, Kostich MS (2013) A validation study of a rapid field-based rating system for discriminating among flow permanence classes of headwater streams in South Carolina. *Environmental Management* 52: 1286–1298.

Golden HE, Sander HA, Lane CR, Zhao C, Price K, D'Amico E, Christensen JR (2016) Relative effects of geographically isolated wetlands on streamflow: a watershed-scale analysis. *Ecohydrology* 9(1): 21-38.

Julian JP, Elmore AJ, Guinn SM (2012) Channel head locations in forested watersheds across the mid-Atlantic United States: a physiographic analysis. *Geomorphology* 177-178: 194–203.

Koskelo AI (2008) Hydrologic and biogeochemical storm response in Choptank basin headwaters. M.S. Thesis. University of Maryland Center for Environmental Sciences, Horn Point Laboratory.

Lampo M (2014) A validation study of the North Carolina rapid field-based rating system for discriminating flow permanence classes of headwater streams in agriculture basins in Southern Illinois. M.S. Thesis, Southern Illinois University Carbondale.

Lane CR, D'Amico E, Autrey B (2012) Isolated wetlands of the Southeastern United States: abundance and expected condition. *Wetlands* 32: 753–767.

Lang M, McDonough O, McCarty G, Oesterling R, Wilen B (2012) Enhanced detection of wetland-stream connectivity using lidar. *Wetlands* 32: 461–473.

Lang M, McCarty G, Oesterling R, Yeo I-Y (2013) Topographic metrics for improved mapping of forested wetlands. *Wetlands* 33: 141–155.

Leahy PP, Martin M (1993) Geohydrology and simulation of ground-water flow in the
Northern Atlantic Coastal Plain Aquifer System: U.S. Geological Survey
Professional Paper 1404-K, 81 p.

Lee, IA, Preacher KJ (2013, September) Calculation for the test of the difference between
two dependent correlations with one variable in common [Computer software].
Available from http://quantpsy.org (last accessed 22 June 2016).

Leibowitz SG (2003) Isolated wetlands and their functions: an ecological perspective.
Wetlands 23(3): 517–531.

Leibowitz SG, Nadeau T-L (2003) Isolated wetlands: state-of-the-science and future
directions. *Wetlands* 23: 663–684.

Leibowitz SG, Wigington PJ, Rains MC, Downing DM (2008) Non-navigable streams
and adjacent wetlands: addressing science needs following the Supreme Court's
Rapanos decision. *Frontiers in Ecology and the Environment* 6(7): 366–373.

Lide RF, Meentemeyer VG, Pinder JE, Beatty LM (1995) Hydrology of a carolina bay
located on the upper coastal plain of western South Carolina. *Wetlands* 15: 47–57.

Likens GE, J. Zedler, B. Mitsch, R. Sharitz, J. Larson, L. Fredrickson, S. Pimm, R.
Semlitsch, C. Bohlen, C. Woltemade, M. Hirschfeld, J. Callaway, T. Huffman, T.
Bancroft, K. Richter, J. Teal, and the Association of State Wetland Managers (2000)
Brief for Dr. Gene Likens et al. as Amici Curiae on Writ of Certiorari to the United
States Court of Appeals for the Seventh Circuit. Solid Waste Agency of Northern
Cook County v. U.S. Army Corps of Engineers, No. 99–1178. Submitted by T. D.
Searchinger and M. J. Bean, attorneys for Amici Curiae.

Lindsay JB, Creed IF, Beall FD (2004) Drainage basin morphometrics for depressional
landscapes. *Water Resources Research* 40: 1–9.

Maryland Department of the Environment (2011) Corsica River Targeted Initiative
Progress Report: 2005 – 2011:
http://www.mde.state.md.us/programs/Water/319NonPointSource/Documents/Corsi
ca_report.pdf (last accessed 03 Jan 2016).

Matisziw TC, Alam M, Trauth KM, Inniss EC, Semlitsch RD, McIntosh S, Horton J
(2015) A vector approach for modeling landscape corridors and habitat connectivity.
Environmental Modeling & Assessment 20: 1–16.

McCarty GW, McConnell LL, Hapeman CJ, Sadeghi A, Graff C, Hively WD, Lang MW,
Fisher TR, Jordan T, Rice CP, Codling EE, Whitall D, Lynn A, Keppler J, Fogel ML
(2008) Water quality and conservation practice effects in the Choptank River
watershed. *Journal of Soil and Water Conservation* 63(6): 461-474.

McLaughlin DL, Kaplan DA, Cohen MJ (2014) A significant nexus: geographically isolated wetlands influence landscape hydrology. *Water Resour. Res.* 50: 7153–7166.

McDonough OT, Lang MW, Hosen JD, Palmer MA (2015) Surface hydrologic connectivity between Delmarva bay wetlands and nearby streams along a gradient of agricultural alteration. *Wetlands* 35: 41–53.

Mitsch WJ, Goselink JG (2000) The value of wetlands: importance of scale and landscape setting. *Ecological Economics* 35: 25–33.

Montgomery DR, Dietrich WE (1988) Where do channels begin? *Nature* 336(6196): 232-234.

Mushet DM, Calhoun AJK, Alexander LC, Cohen MJ, DeKeyser ES, Fowler L, Lane CR, Lang MW, Rains MC, Walls SC (2015) Geographically isolated wetlands: rethinking a misnomer. *Wetlands* 35:423-431.

Nadeau T-L, Rains MC (2007) Hydrological connectivity between headwater streams and downstream waters: how science can inform policy: hydrological connectivity between headwater streams and downstream waters: how science can inform policy. *JAWRA* 43: 118–133.

Nippgen F, McGlynn BL, Marshall LA, Emanuel RE (2011) Landscape structure and climate influences on hydrologic response. *Water Resources Research* 47: 1–17.

Natural Resources Conservation Service (NRCS) 2007. "National Engineering Handbook Chapter 7 Hydrologic Soil Groups." *Hydrology National Engineering Handbook*.

O'Brien RM (2007) A caution regarding rules of thumb for variance inflation factors. *Quality & Quantity* 41: 673-690.

Phillips PJ, Denver JM, Shedlock RJ, Hamilton PA (1993) Effect of forested wetlands on nitrate concentrations in ground water and surface water on the Delmarva Peninsula. *Wetlands* 13: 75–83.

Phillips PJ, Shedlock RJ (1993) Hydrology and chemistry of groundwater and seasonal ponds in the Atlantic Coastal Plain in Delaware, USA. *Journal of Hydrology* 141: 157–178.

Pringle CM (2001) Hydrologic connectivity and the management of biological reserves: a global perspective. *Ecological Applications* 11(4): 981–998.

Pringle C (2003) What is hydrologic connectivity and why is it ecologically important? *Hydrological Processes* 17: 2685–2689.

Prouty WF (1952) Carolina Bays and their origin. *Geological Society of America Bulletin* 63: 167–224

Pyzoha, JE, Callahan, TJ, Sun G, Trettin CC, Miwa M (2008) A conceptual hydrologic model for a forested Carolina bay depressional wetland on the Coastal Plain of South Carolina, USA. *Hydrol. Processes* 22(14): 2689–2698.

Rains MC, Leibowitz SG, Cohen MJ, Creed IF, Golden HE, Jawitz JW, Kalla P, Lane CR, Lang MW, McLaughlin DL (2016) Geographically isolated wetlands are part of the hydrological landscape. *Hydrol. Process* 30: 153-160.

Sharitz RR, Gibbons JW (1982) The ecology of southeastern shrub bogs (pocosins) and Carolina Bays: a community profile. FWS/OBS-82/ 04. US Fish and Wildlife Service, Division of Biological Services, Washington, DC

Sharitz RR (2003) Carolina bay wetlands: Unique habitats of the southeastern United States. *Wetlands* 23(3): 550–562.

Shaw DA, Pietroniro A, Martz LW (2013) Topographic analysis for the prairie pothole region of Western Canada. *Hydrological Processes* 27(2): 3105-3114.

Snodgrass JW, Bryan AL, Lide RF, Smith GM (1996) Factors affecting the occurrence and structure of fish assemblages in isolated wetlands of the upper coastal plain, U.S.A. *Canadian Journal of Fisheries and Aquatic Sciences* 53: 443-454.

Snodgrass J, Komoroski M, Bryan AL, Burger J (2000) Relationships among isolated wetland size, hydroperiods, and amphibian species richness: implications for wetland regulations. *Conservation Biology* 14: 414–419.

Svec JR, Kolka RK, Stringer JW (2005) Defining perennial, intermittent, and ephemeral channels in Eastern Kentucky: Application to forestry best management practices. *Forest Ecology and Management* 214: 170–182.

Tarboton DG (1997) A new method for the determination of flow directions and upslope areas in grid digital elevation models. *Water Resources Research* 33(2): 309-319.

Tarboton DG, and Ames DP (2001) Advances in the mapping of flow networks from digital elevation data. Proceedings of the World Water and Environmental Resources Congress, Orlando, Florida.

Taylor PD, Fahrig L, Henein K, Merriam G (1993) Connectivity is a vital element of landscape structure. *Oikos* 68(3): 571–573.

Theriot JM, Conkle JL, Pezeshki SR, DeLaune RD, White JR (2013) Will hydrologic restoration of Mississippi River riparian wetlands improve their critical biogeochemical functions? *Ecological engineering* 60: 192-198.

Tiner RW (2003) Geographically isolated wetlands of the United States. *Wetlands* 23(3): 494–516.

Tiner RW (2010) Wetland Hydrology. Biogeochemistry of Inland Waters.

Turner DS, Richter HE (2011) Wet/dry mapping: using citizen scientists to monitor the extent of perennial surface flow in dryland regions. *Environmental Management* 47: 497–505.

USEPA (US Environmental Protection Agency) (2015) Connectivity of streams and wetlands to downstream waters: a review and synthesis of the scientific evidence. EPA/600/R-14/475F. US Environmental Protection Agency, Washington, DC.

USEPA and USACE (US Environmental Protection Agency and US Army Corps of Engineers) (2015) Clean Water Rule: definition of "Waters of the United States". 80 Fed. Reg. 37054 (June 29, 2015).

Willgoose C, Hancock G (1998) Revisiting the hypsometric curve as an indicator of form and process in transport-limited catchment. *Earth Surface Processes and Landforms* 23: 611–623.

Winter TC (1988) A conceptual framework for assessing cumulative impacts on the hydrology of nontidal wetlands. *Environmental Management* 12: 605–620.

Winter TC (2001) The concept of hydrologic landscapes. *JAWRA* 37(2): 335–349.

Winter TC, LaBaugh JW (2003) Hydrologic considerations in defining isolated wetlands. *Wetlands* 23: 532–540.

Wolock DM, Winter TC, McMahon G (2004) Delineation and evaluation of hydrologic-landscape regions in the United States using geographic information system tools and multivariate statistical analyses. *Environmental Management* 34(S1): S71–S88.

Wolman MG, Miller JP (1960) Magnitude and frequency of forces in geomorphic processes. *The Journal of Geology* 68(1): 54-74.

Yuan J, Cohen MJ, Kaplan DA, Acharya S, Larsen LG, Nungesser MK (2015) Linking metrics of landscape pattern to hydrological process in a lotic wetland. *Landscape Ecology* 30: 1893–1912.

Zedler, JB, Kercher S (2005) Wetland resources: status, trends, ecosystem services, and restorability. *Annu. Rev. Environ. Resour.* 30: 39-74.