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Relative effects of geographically isolated wetlands on streamflow: a watershed-scale analysis

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ABSTRACT

Geographically isolated wetlands (GIWs) are characterized as 'isolated' because they are embedded by uplands, though they potentially exhibit a gradient of hydrologic, biological, or chemical connections to other surface waters. In fact, recent field studies have begun to elucidate that GIWs exhibit varying degrees of hydrologic connectivity. In this study, we examine the influence of GIWs on streamflow, a potential indicator of GIW hydrologic connectivity with surface waters. We assess annual and seasonal spatially based statistical relationships between GIW characteristics (e.g. volume and extent) and streamflow across a dense network of subbasins using a hybrid modeling approach. Our method involves the Spatial Stream Network (SSN) model, which considers spatial autocorrelation of model covariates explicitly, and the Soil and Water Assessment Tool (SWAT), which predicts streamflow across a network of 579 subbasins in the lower Neuse River Basin, North Carolina, USA. Our study results suggest that GIWs, to some extent, influence streamflow. The further GIWs are from a stream, the greater their capacity to increase streamflow due to the physiographic setting, hypothesized transit times, and sequencing of watershed hydrologic connectivity in the study area. However, as the combined extent of GIWs and non-GIWs increases in subbasins, seasonal and annual streamflow decreases. Results also suggest that other landscape indicators of watershed-scale hydrology can, in aggregate with GIWs and non-GIWs, explain variations in seasonal and annual simulated streamflow. Our study findings begin to elucidate the aggregate influence of GIWs on streamflow, providing insights for future decision-making on GIW protection and management. Copyright © 2015 John Wiley & Sons, Ltd.

KEY WORDS geographically isolated wetlands; wetlands; hydrologic connectivity; watershed; hydrology; watershed model; spatial stream network model

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INTRODUCTION

Wetlands provide important ecosystem functions and services including flood regulation, fish and fiber production, water supply sources, recreation, water purification, and coastal protection (Millennium Ecosystem Assessment, 2005). Despite their potential benefits, the explicit consideration of wetlands in watershed management and planning processes is often secondary to other water bodies (e.g. streams, river, and lakes). This limited focus on wetlands as mediators and providers of a wide range of ecosystem services coincides with the approximately 30–90% decline in the world's wetland spatial coverage by activities such as conversion of wetland areas for urban development and agriculture (Junk *et al.,* 2013).

Geographically isolated wetlands (GIWs) are distinguishable as depressional landscape features that are entirely surrounded by uplands and include water body types such as prairie potholes, playa lakes, vernal pools, pocosins, Carolina bays, and cypress domes (Brinson, 1988; Tiner, 2003a). This nomenclature does not necessarily imply functional isolation because these systems may exhibit a gradient of hydrologic, biological, or chemical connections to other surface waters (Mushet *et al*., 2015). For example, in some situations and/or settings, GIWs have shown clear hydrologic connectivity with other surface water systems (e.g. Leibowitz and Vining, 2003; Wilcox *et al.,* 2011; Forbes *et al.,* 2012). However, our scientific understanding regarding the hydrologic connectivity of GIWs and their effects on

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downstream hydrology is limited to case-specific studies and key questions regarding their aggregate impacts on ecological and watershed functions remain unexplored (Leibowitz, 2003; Leibowitz *et al.,* 2008).

Geographically isolated wetlands have been a primary focus in regulatory efforts within the United States (US). Two US Supreme Court cases, the 2001 *Solid Waste Agency of Northern Cook County (SWANCC) v. the United States (US) Army Corps of Engineers, 531 U.S. 159,* and *Rapanos v. United States 547 U.S.715 (2006)*, suggest that protection can be afforded to GIWs under the US Clean Water Act in situations where a significant nexus between GIWs and traditional navigable waters can be identified. As a result of these Supreme Court decisions, decision makers have been handed a critical challenge to which science and engineers must respond: To what extent are GIWs connected to or demonstrate an effect on traditional navigable waters (Leibowitz *et al.,* 2008)? A first step toward addressing this challenge is to quantify the potential hydrologic influence of GIWs on downstream surface waters.

Abundant field-based studies provide important insights on hydrologic connectivity within hillslopes and small watersheds (e.g. James and Roulet, 2007; Hopp and McDonnell, 2009; Jencso *et al.,* 2009; McGuire and McDonnell, 2010). Further, literature are available that quantify linkages between non-GIWs and streamflow (Johnston *et al.,* 1990; Vining, 2002) and variations in the hydrologic regime of individual GIWs (McLaughlin and Cohen, 2013; 2014). However, studies that assess the hydrologic effects of GIWs on surface waters at a range of watershed scales are limited (e.g. Wilcox *et al.,* 2011; Lang *et al.,* 2012), in part because elucidating these linkages is particularly challenging. First, potential connectivity via surface and groundwater is highly variable across space and time, physiographic settings, and ecoregions (Winter and LaBaugh, 2003). For example, variations in connectivity can result from multiple factors relating to landscape position such as the hydraulic gradient between the GIW and the stream, the distance of the GIW to the stream, and fill-spill dynamics between wetlands (e.g. wetland volumes can increase ('fill') from runoff contributed by upgradient wetlands and decrease in volume by contributing runoff (i. e. wetlands 'spill') into downgradient wetlands (Leibowitz and Vining, 2003)). Such variables can affect (1) the potential impact of that wetland or wetland complex on the hydrograph and (2) detection of that effect using empirical or modeling methods. Second, hydrologic connectivity can be expressed via multiple pathways including but not limited to shallow subsurface flows (Sun *et al.,* 1996; Pyzoha *et al.,* 2008), overland flow (Wilcox *et al.,* 2011), groundwater flow (Winter and LaBaugh, 2003), and perched groundwater discharge (Rains *et al.,* 2006) – all of which may occur in any given GIW complex over the course of a given year (e.g. Sun *et al.,* 1995; Devito *et al.,* 1997). Finally, limited data exist that elucidate these hydrologic connections across seasonal or annual time scales (e.g. Cook and Hauer, 2007; Wilcox *et al.,* 2011).

Statistical models are important tools for identifying the potential influences of GIWs on downstream hydrology at the watershed scale and for providing improved parameter estimates for dynamic simulation models that address similar questions (Golden *et al.,* 2014). The first step in developing such models involves identifying watersheds with extensive GIW coverage (Tiner, 2003b). Coastal Plain systems (Omernik, 1987), for example, are areas where depressional wetlands systems are common (Pyzoha, 2008) and thus are prime study areas for testing and assessing the effects of GIWs on downstream hydrology. A second step involves identifying a time series of hydrologic data from multiple subbasins within the larger watershed system to evaluate these statistical linkages between GIWs and downstream flow conditions. These flow conditions can be obtained from mechanistic hydrologic models that simulate watershed runoff and streamflow by using mathematical formulations and structured calibration methods (National Research Council, 2007).

The objective of this study is to examine the watershed-scale aggregate influence of GIWs on streamflow. Specifically, we analyse the spatially based statistical relationships between simulated streamflow, the response variable, and GIW characteristics (e.g. volume, extent, and type) across a dense network of subbasins using a hybrid-modeling approach. This constitutes one of the first known studies to investigate the role of watershed GIWs on the downstream hydrograph. Our work focuses on an area of approximately 6570 km^2 within the lower Neuse River Basin of North Carolina, USA, a Coastal Plain system with a high density of mapped GIWs (Lane *et al.,* 2012) and simulated hydrologic time series data from 579 subbasins ranging in area from 1.4 to 37.3 km^2 (Price *et al.,* 2013). The hybrid statistical and mechanistic modeling approach we employ incorporates a recently developed geostatistical model (Peterson and Ver Hoef, 2010; Ver Hoef and Peterson, 2010a, b) with an established hydrologic modeling tool (Soil and Water Assessment Tool (SWAT); Gassman *et al.,* 2007) that simulates streamflow at each subbasin outlet. We analyse streamflow as a response variable using annual and seasonal geostatistical models that represent the configuration, connectivity, and flow direction of stream networks. Model predictor variables include the volume, type, and extent of GIWs and non-GIWs, in addition to a parsimonious array of landscape indicators of watershed rainfall-runoff processes and groundwater flow. We interpret the effects of GIWs on streamflow via potential hydraulic gradients and hydrologic connections; however, for the purposes of this paper, we term all downgradient and downstream hydrograph responses as 'downstream' effects. The results from this study provide important insights on the hydrologic connectivity of GIWs to surface waters and afford an improved mechanistic understanding of the relationships among GIWs and other surface waters in the hydrologic landscape.

METHODS AND MATERIALS

Study area

The Neuse River Basin is located within the Middle Atlantic Coastal Plain ecoregion in North Carolina, USA (Omernik, 1987). Our study area covers approximately 6570 km^2 in the lower Neuse River Basin within the boundaries of the North Carolina Coastal Region Evaluation of Wetland Significance Study (NC-CREWS; Figure 1; Sutter, 1999). The Neuse River Basin covers two physiographic provinces: the Piedmont and the Coastal Plain. However, our study area lies entirely within the Coastal Plain portion of the basin. We chose this particular region of the Neuse River Basin to utilize locally derived wetland types from NC-CREWS for the Coastal Plain of North Carolina (described in *GIWs: Identification and volume calculations*).

The study watershed has undergone considerable management attention in recent years due to rapid human-influenced changes in hydrology and nutrient loading (Paerl *et al.,* 2006; Rothenberger *et al.,* 2009). Based on the 2006 National Land Cover Database obtained from the Multi-Resolution Land Characteristics Consortium (Fry *et al.,* 2011), land cover is predominately agricultural (41%), forested (20%), and covered by wetlands (17%). However, portions of the study area are developed (10%) or include grassland/herbaceous cover

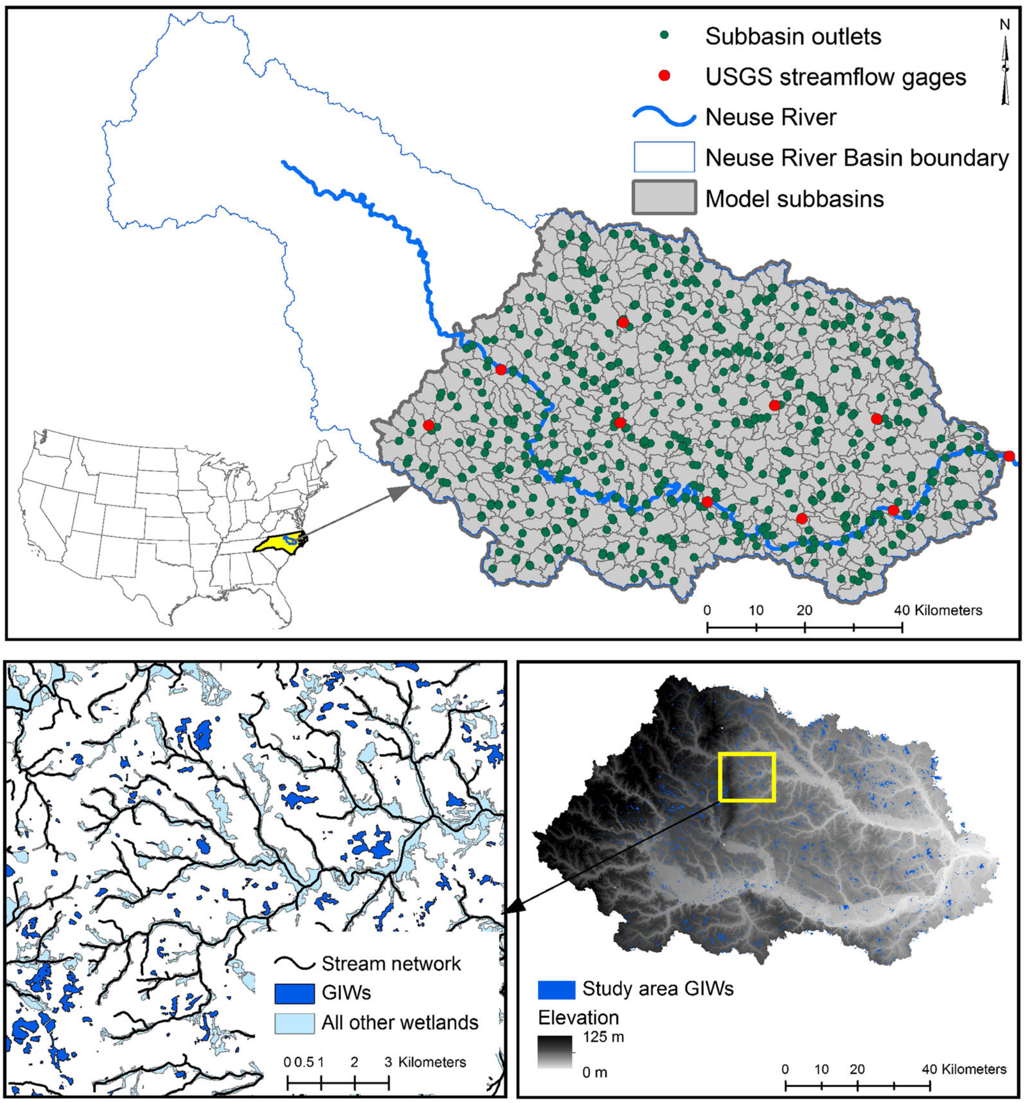

Figure 1. Study area and example distribution of wetlands in the 579 study subbasins in the lower Neuse River Basin, North Carolina.

(5%), shrub/scrub (5%), and other land cover types (2%). The NC-CREWS data suggest that the freshwater wetland types with the most extensive coverage within the study area are bottomland hardwoods wetlands, managed pineland wetlands, and riverine swamp forests (Sutter, 1999). Dominant GIW wetland types include depressional swamp forest wetlands, drained hardwood flats, drained pine flats, nondrained hardwood flats, and managed pineland wetlands.

The study area climate is humid temperate. Climate normals (1981–2010) recorded at three of the primary weather stations in the study area (Kinston, NC; Goldsboro Seymour Johnson AFB, NC; and Clayton, NC) suggest that the highest average precipitation occurs during the summer months and the lowest during winter (NCDC, 2011). However, high rainfall and streamflow periods can occur throughout the year (Figure 2). Mean temperatures during summer months (June through September) at these three weather stations range from 25°C to 26°C. Summer precipitation averages range from approximately 37 cm to 42 cm. Late summer and early autumn tropical storm events are often in high intensity and can collectively influence regional streamflows (Keim *et al.,* 2007). Average winter temperatures (January through March) range from 5°C to 7°C, and mean winter precipitation is approximately 26 cm at all stations (NCDC, 2011).

The Coastal Plain portion of the Neuse is underlain by clastic alluvial and marine sediments (Walker and Coleman, 1987; Leigh, 2008). In a small portion in the upper northwest of the study area, coarse, unconsolidated materials promote high rates of infiltration and shallow subsurface transport (Ator *et al.,* 2005). However, in the majority of our study area, sediment textures are mixed and vary laterally and horizontally from coarse sands to clays and silts. Wetlands in this area and in the uplands throughout the Neuse River Basin are often underlain by a clay confining layer, affording limited wetland-based opportunities for groundwater recharge and contributions to subsurface transport. Warm temperatures and abundant vegetation result in annually high evapotranspiration (ET) rates; approximately 51% of regional annual precipitation is lost to evapotranspiration (Ator *et al.,* 2005). Elevation ranges across the study area from 0 m to 125 m above mean sea level. Slopes within the study area's subbasins average 2.6% and range from 0.56% in the lower study area to 8.3% in the upper portion of the study area. There are no significant areas of karst within the Neuse system.

Conceptualized wetland hydrologic processes in the study area

Soils, surficial geology, and wetland hydrologic characteristics can vary widely across small spatial extents and the hydrologic and hydraulic processes resulting from these variations can be quite complex. However, for the purposes of this study and the large spatial extent it encompasses, we developed a generalized conceptual model for wetland hydrological processes across this watershed area and the seasonal and annual time scales we examine in order to proceed with the selection of model input variables and the analysis of model results. The study area includes abundant GIW and non-GIW wetlands and wetland complexes, many of which are elliptical depressions oriented in a northwest-southeastern direction (i.e. Carolina bays; Ross,

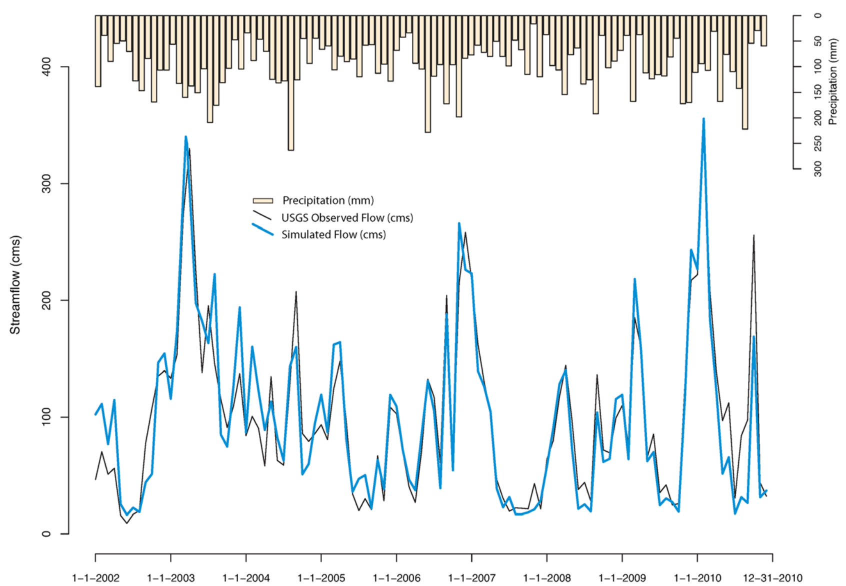

Figure 2. Monthly precipitation, SWAT-simulated streamflow at USGS 02091814 Neuse River at Fort Barnwell gage (outlet of the study area), and the observed streamflow at USGS 02091814.

2003; Sharitz, 2003). Wetlands in this area of the Coastal Plain, and within our study area in particular, typically exhibit soils with sandy loams underlain by a low permeability clay layer and can also have a sandy rim and sandy soils in the adjacent uplands (Sharitz and Gibbons, 1982). Deep groundwater connections from the GIW upland areas to downgradient streams in the study are limited because of the relatively low topographic gradients, low soil permeability, and clayey confining layers underneath the sandy loam soils (Heath, 1980), particularly when undisturbed (e.g. nondrained) conditions exist (Sharitz and Gibbons, 1982; Sharitz, 2003). Thus, precipitation, evapotranspiration, and return, shallow subsurface, and surface flows in and out of the wetlands are the primary hydrologic processes governing these wetland and wetland complexes. The magnitude of these processes can vary across seasons and years based on factors such as temperature, precipitation, and long-term drought or wetness conditions. GIWs and other upland wetlands in the study area may exhibit a fill-spill mechanism similar to the Prairie Pothole Region (PPR) of North America (Shaw *et al.,* 2012) because while climate, geology, and soils are vastly different between the two regions, our study area and the PPR have similarly abundant wetland distribution across the landscape, low slope gradients, and limited deep groundwater exchanges. Further, because localized shallow subsurface flow patterns may exist where the study wetlands and wetland complexes are located, potential mounding from the shallow water table may also occur because of the seasonally strong (e.g. spring and summer) evapotranspiration rates in these systems (Winter and LaBaugh, 2003).

SWAT watershed delineations and hydrologic simulations

We applied the Soil and Water Assessment Tool (SWAT) 2009 (Neitsch *et al.,* 2011) to predict streamflow for each of the study subbasins (Sharitz and Gibbons, 1982). We summarized daily simulated streamflow for each of the subbasins into mean seasonal and mean annual streamflow (Figure 3), and these data were used as the response variables for our geostatistical models. To develop the study subbasins, we first generated the stream network during SWAT preprocessing using a 30 m digital elevation model (Price *et al.,* 2013), a scale computationally appropriate for the application of the SWAT model in a drainage area of this size. We then divided the area into 579 topographically defined subbasins using SWAT, each containing GIWs covering > or = 1% spatial extent (Table I). The study subbasins average drainage area was 11.4 km^2 (5.8 km^2 standard deviation, SD) with ranges from 1.4 km^2 to 37.3 km^2. We then split each subbasin into hydrologic response units (HRUs) in which all pixels sharing the same combined land cover, soils, and slope

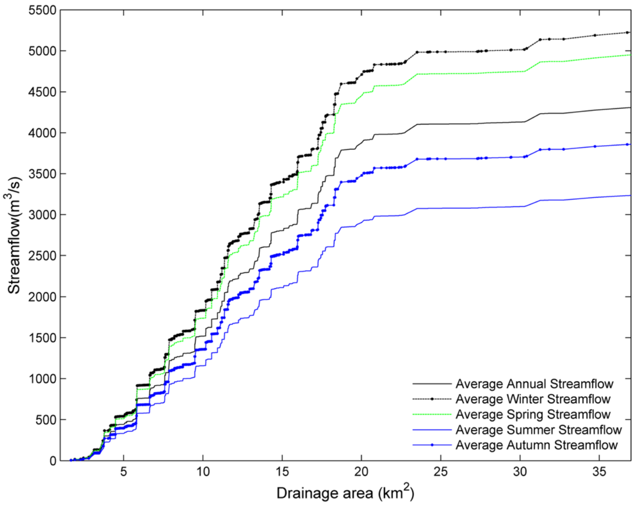

Figure 3. Cumulative SWAT-simulated average annual and seasonal streamflow across the 579 study subbasins.

class are simulated with a uniform flow response. We diagnosed potential nonspatial linear relationships of land cover, soils, and slope with annual and seasonal streamflow using Spearman rank correlation coefficients. Results showed either no significant or weakly significant ($r < 0.24$) nonspatial correlations between these factors and streamflow.

We used meteorological data (daily precipitation, maximum and minimum temperatures for the study period (2001–2010) from the National Climate Data Center (NCDC) or North Carolina CRONOS database (NCDC, 2011; State Climate Office of North Carolina, 2011) and SWAT assigned daily values to each subbasin based on the data station within closest proximity to the subbasin centroid. We excluded stations missing greater than 10% of daily observations; missing values were obtained from the next closest station (Ngongondo *et al.,* 2011). We selected all default options for the SWAT simulations except that the Hargreaves equation for evapotranspiration was substituted for the default Penman–Monteith equation. Hargreaves produced more accurate uncalibrated fits between simulated and observed flows, particularly with low flows, which have been observed in other studies applying SWAT (Wang *et al.,* 2006; Setegn *et al.,* 2008).

We calibrated and validated SWAT using a split-sample approach (Klemes, 1986; Price *et al.,* 2012), dividing the period of record (2002–2010) into a calibration period (2002–2007) and a validation period (2008–2010) from daily US Geological Survey (USGS) stream gage time series data. Calibration was conducted at the stream gage at the outlet of the study area (Figure 1). Our calibration approach was to find the set of SWAT parameters that resulted in the maximum Nash–Sutcliffe Efficiency score:

Table I. Watershed-scale variables included in models.

Variable group	Variables	Mean	Minimum	Maximum	Standard deviation
Streamflow	Streamflow (average annual mean daily – m^3/s)	7.45	0.04	147.28	21.51
	Streamflow (average winter mean daily – m^3/s)	9.03	0.05	174.56	25.92
	Streamflow (average spring mean daily – m^3/s)	8.55	0.05	164.49	24.57
	Streamflow (average summer mean daily – m^3/s)	5.59	0.02	116.24	16.27
	Streamflow (average autumn – m^3/s)	6.67	0.02	134.88	19.49
Wetlands					
All wetlands (NC-CREWS)	All wetland types per subbasin area (%)	15.46	1.00	90.22	10.41
Geographically isolated wetlands	GIWs per subbasin area (%)	26.55	1.00	26.55	29.21
(NC-CREWS-based estimate)	Subbasin area flowing into GIWs (%)	12.54	0.01	94.95	10.21
	Ln(total GIW volume (m^3))	14.13	5.70	17.29	1.54
Dominant GIW	Depressional swamp forest (%)	0.10	0.00	4.43	0.29
NC-CREWS classes	Drained pine flat (%)	0.14	0.00	8.51	0.54
	Drained hardwood flat (%)	0.16	0.00	8.40	0.64
	Managed pineland (%)	1.54	0.00	11.79	1.79
	Pine flat (%)	0.19	0.00	11.00	0.72
Dominant overall wetland	Managed pineland (%)	3.05	0.00	39.26	3.63
NC-CREWS classes (non-GIW and GIWs)	Riverine swamp forest (%)	5.20	0.00	51.37	6.66
	Bottomland hardwood (%)	3.27	0.00	32.43	4.04
Wetlands from	Woody wetlands (%)	16.00	0.54	73.54	10.18
NLCD 2006 land cover	Emergent herbaceous wetlands (%)	1.21	0.00	21.91	1.99
Distance measure	Average distance from GIW to stream (m); (median = 1973.8 m)	2044.3	95.0	6175.4	911.3
Watershed-scale soil moisture inputs					
Precipitation	Precipitation (average total annual – mm)	1231.0	914.9	1427.6	95.1
	Precipitation (average total winter – mm)	247.0	190.1	265.4	9.9
	Precipitation (average total spring – mm)	294.8	222.3	335.0	20.3
	Precipitation (average total summer – mm)	408.0	240.2	510.0	51.0
	Precipitation (average total fall – mm)	281.2	231.3	331.7	23.6
Watershed-scale surface and shallow subsurface runoff					
Stream density and slope measures	Stream density (NHD 1:24000 resolution) (m/m^2)	0.002	0.0003	0.004	0.001
	Mean subbasin slope (%)	2.64	0.56	8.25	1.46
Hydrologic soil group (HSG)	HSG A (%)	15.30	0.00	77.20	16.40
	HSG D (%)	29.33	3.08	91.30	13.37
Land Cover – NLCD 2006	Open water (%)	1.06	0.00	28.51	2.28
	Developed, open space (%)	6.36	0.00	54.04	5.40
	Developed, low intensity (%)	2.25	0.00	38.60	4.59
	Developed, medium/high intensity (%)	1.02	0.00	26.39	2.95
	Barren land (rock/sand/clay) (%)	0.28	0.00	16.26	1.24
	Deciduous forest (%)	6.52	0.00	43.80	8.50
	Evergreen forest (%)	11.29	0.08	51.89	6.68
	Mixed forest (%)	2.73	0.00	14.08	1.99

	Shrub/scrub (%)	4.98	0.00	24.69	4.43
	Grassland/herbaceous (%)	5.46	0.10	24.44	4.34
	Pasture/hay (%)	5.25	0.00	26.48	5.51
	Cultivated crops (%)	35.61	0.55	74.18	15.09
Groundwater contributions					
Groundwater	Average baseflow index (BFI) in subbasin (%)	39.43	29.50	46.39	2.84

$$NSE = 1 - \frac{\sum_{t=1}^{n} (O_t -, S_t)^2}{\sum_{t=1}^{n} (O_t - \bar{O})^2}$$

where O_t is the observed streamflow ($L^3\ T^{-1}$), $\bar{O}$ is the mean of the observed streamflow ($L^3\ T^{-1}$), and S_t is the simulated streamflow ($L^3\ T^{-1}$). Calibration achieved a maximum NSE score of 0.85 for monthly streamflow (Figure 2). We performed validation using these NSE-optimized parameter values by comparing simulated flows for 2008–2010 with USGS-observed flows at the main study area outlet, for which the monthly NSE score was 0.87 (Figure 2). We also performed validation by comparing observed and simulated flows from nine gaging stations inside the study area (Figure 1). Average monthly and annual R^2 values at these internal cross-check gages were 0.69 and 0.85 ($p < 0.05$), respectively, for upstream drainage areas that averaged 2438 km^2 (range = 150 to 6972 km^2, the largest of which extends approximately 402 km^2 above our study area).

Model predictor variables

Geographically isolated wetlands: identification and volume calculations. We used the NC-CREWS dataset for delineating potential GIWs in the study area and identifying all other nonisolated wetlands. These data represent the most recent National Wetlands Inventory (NWI)-enhanced spatial data for wetlands in the study area (Sutter, 1999). Further details regarding the development and quality assurance procedures of the NC-CREWS dataset, which involves a multiphase combination of NWI, county soils, and land use/land cover data, can be found from the North Carolina Division of Coastal Management (DCM) (Sutter, 1999; www.nccoastalmanagement.net/Wetlands/Wetlands_meta.htm, accessed 13 February 2014).

We delineated potential GIWs within the study using a multiple step methodology described in Reif *et al.* (2009) and Frohn *et al.* (2009) (Figure 1, bottom left). Briefly, we first aggregated the NC-CREWS wetland data so that nested polygons were treated as a single wetland, though each wetland retained its original area-weighted classification. This was necessary to ensure that the entire wetland would be selected if any portion of it was designated as nonisolated. Next, we followed Reif *et al.* (2009) and Lane *et al.* (2012) and created a 10 m buffer area around 1 : 24000-scale flowline, waterbody, and water area datasets from the National Hydrography Dataset (NHD; http://nhd.usgs.gov/index.html). While NHD flowline connectors, paths, and unnamed artificial paths were removed from the NHD flowline prior to buffering, artificial paths with names (which tend to represent larger creeks and rivers rather than pathways through large lakes or ponds) were included in the buffering process. We also included NHD canals and ditches in the buffer analysis since they often represent irrigated areas. Wetlands outside of the conservative 10 m buffered area were considered 'geographically isolated'. We identified nonisolated wetlands by overlaying the GIW layer on the NC-CREWS dataset for the study area. We then estimated the percent of all GIW types per subbasin and the percent dominant types of nonisolated wetlands for each of the 579 subbasins and used in these variables as predictor variables to the geostatistical model (Table I). We note that our methodology may classify wetlands as 'isolated' that are potentially connected to other unmapped surface waters (e.g. via ditching). Though we use the term 'geographically isolated', we recognize that these wetlands are, in fact, presumed GIWs based on tested spatial analytical techniques (Lane *et al.* 2012).

We calculated wetland volumes following the methodology presented in Lane and D'Amico (2010) using 3 m pixel size Light Detecting and Ranging (LiDAR) data collected between January and March 2001, acquired by direct transfer from the North Carolina Division of Emergency Management Floodplain Mapping Program in 2011 (see Floodplain Mapping Program, North Carolina Division of Emergency Management Neuse River LIDAR metadata, available from http://floodmaps.nc.gov for additional information [accessed 30 January 2014]). We first built a digital terrain from the bare earth LiDAR data using ArcGIS10 (ESRI Corporation, Redlands CA) 3D Analyst (Figure 1, lower right). We then calculated the average perimeter elevation for all of the GIWs by converting the boundary of the GIWs to vertices then running the Surface Information Tool in ArcGIS 10 to gather the Z value (elevation from the 3 m National Elevation Data (NED) available for North Carolina from the USGS (http://ned.usgs.gov/) for each of the vertices. By summarizing the vertices for each and then dividing the value by the number of vertices, we were able to calculate the average perimeter elevation; more complex GIWs had more vertices (see Lane and D' (2010) for additional information). We used this average perimeter elevation as the stage-height elevation value in volume calculations. Using the Polygon Volume model in ArcGIS 3D Analyst, we then calculated volume for each of the GIWs, following the assumption that the digital terrain used for calculating perimeter elevations represents dry wetland conditions (to avoid the underestimation of wetland volumes). Finally, we calculated the total GIW volume for each subbasin as an input variable to the models (Table I). Factors that describe the potential for water to flow from a GIW to the stream are detailed in the *Watershed-scale variables* section.

Watershed-scale variables. We incorporated indicators of soil wetness, surface and shallow subsurface runoff, and groundwater contributions that could affect streamflow, along with average GIW and non-GIW volume, area, distances, and percent dominant wetland types within both categories, in our model development (Table I). Variables were derived for each of the 579 subbasins. All GIS analyses for estimating these watershed-scale variables were conducted using ArcGIS10, and a summary of data sources for each derived predictor variable used in this study is listed in the supporting information.

We calculated two variables to estimate the influence of distance and slope on runoff from GIWs to surface waters: (1) average distance from GIWs to the stream along estimated flow paths and (2) average slope of the subbasin. We generated both using the 10 m National Elevation Dataset (http://ned.usgs.gov/) rather than the 3 m LiDAR DEM to stay consistent with the application of publically available national datasets for the derivation of watershed metrics and to minimize computational time for the former metric. We estimated average distance from a given GIW to a stream for each watershed using cost path distance analysis, which involved estimating the hydrologic flow path from the GIW centroids to the closest stream. We also included a metric that estimated the percent of the each subbasin that drains into GIWs. GIWs from NCCREWS and flow direction were combined to identify the upland portions of the watershed that flow through isolated wetlands. We then summed the total area of each subbasin that flowed through GIWs. We calculated stream density per subbasin using the 1 : 24000 NHD Flowlines by summing the total stream length in a basin then dividing by the basin area.

We derived land cover types for each subbasin from the 30 m resolution 2006 National Land Cover Dataset (NLCD) from the Multi-Resolution Land Cover (MRLC) Consortium (Table I; Fry *et al.,* 2011). We calculated the percent of each Hydrologic Soils Group (HSG), as an indicator of soil infiltration, subsurface transmissivity, and runoff potential, for each subbasin using the SSURGO soils database (USDA-NRCS, 2013). Hydrologic Soils Groups are classified into four categories (A, B, C, and D) along a gradient of permeability and runoff potential. We selected the two extremes of the HSGs for analysis: HSG A represents soils with the highest infiltration capacity and lowest runoff potential, and HSG D approximates the inverse. All soils classified as A/D (portions of these soils are classified as 'A' if drained but 'D' if not drained) were reclassified as HSG D for our analyses. These soils averaged <2% of HSGs for the study subbasins.

We averaged the base flow index (BFI), a dataset obtained from Wolock (2003), for each subbasin. The BFI is calculated as the average proportion of annual streamflow that can be attributed to groundwater discharge (expressed as a percentage). The index served as an indicator of subsurface contributions to streamflow in this study.

Geostatistical modeling

We analysed the relationships between GIWs and other watershed-scale indicators of hydrologic processes on streamflow both annually and seasonally. To do this, we diagnosed potential (nonspatial) multicollinearity of the study's predictor variables on streamflow using the variance inflation factor (VIF) in an ordinary least squares regression analysis (Belsey *et al.,* 2004). We then assessed variables with a high variance inflation factor (VIF > 4) using partial correlation analysis. Variables with partial correlations ≥0.40 were removed from the analysis. All analyses were conducted using R statistical software, version 2.14.3 (R Development Core Team, 2012).

We developed seasonal analysis according to the calendar year with the following classifications: winter (January to March), spring (April to June), summer (July to September), and autumn (October to December). Estimating the relationships between GIWs and other explanatory variables with streamflow using ordinary least squares (OLS) regression is problematic given the inherent connectivity of stream networks, which leads to spatial autocorrelation and violates assumptions of independence and makes such statistical models inappropriate. Exploratory data analysis in our study area suggested that average annual simulated streamflow at subbasin outlets is similar in headwaters and in areas along streamflow networks due to nested subbasins (Figure 4). Therefore, spatial autocorrelation was certain to confound OLS analysis. We therefore used a geostatistical modeling methodology designed to account for the spatial dependence often found in stream networks due to their spatial connectivity, flow direction, and flow volume (Peterson and Ver Hoef, 2010; Ver Hoef and Peterson, 2010a, b). This methodology operates based on a moving average (MA) construction that allows for the production of autocovariances that identify the presence of spatial autocorrelation based on hydrologic relationships. Random variables are generated by combining MA constructions with white noise signals. When MA constructions for one random variable overlap those of another, spatial autocorrelation occurs (Ver Hoef and Peterson, 2010a) with larger overlaps indicating greater autocorrelation.

Moving average functions may operate using different network structures. Locations along the network may be considered flow-connected (e.g. when water flows from upstream to downstream locations) or flow-unconnected (e.g. when two points occur in separate tributaries that flow to a common point but are not themselves connected by flow). Covariances may be based on Euclidean

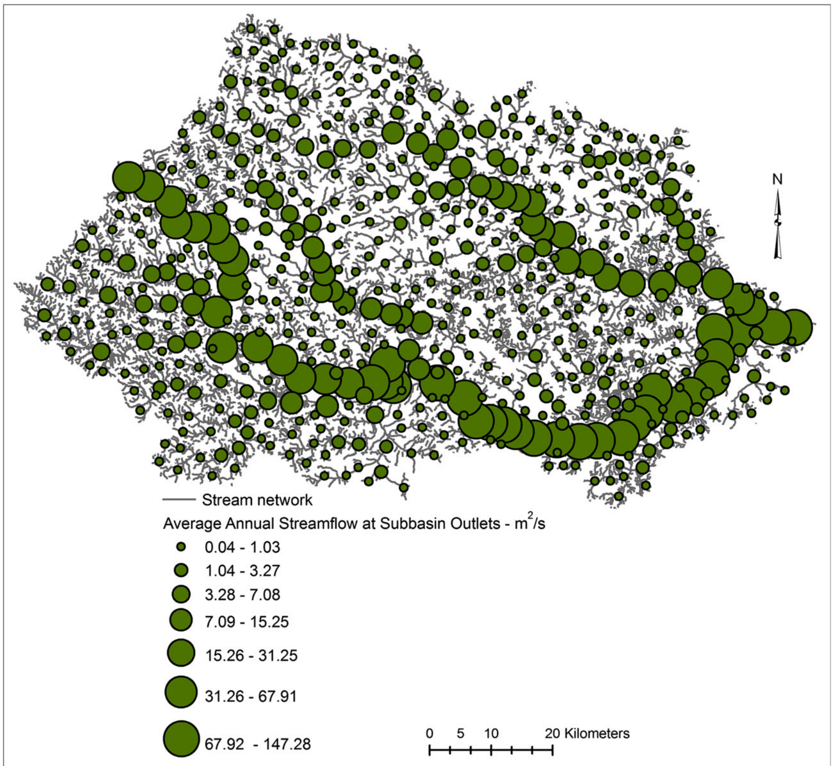

Figure 4. Spatial distribution of average annual SWAT-simulated streamflow across the watershed; shown for the outlets of the 579 study subbasins.

distances that utilize two-dimensional coordinates or on other distances that consider network connectivity. 'Tail-up' covariances are based on stream network distances with spatial autocorrelation of streamflow directed downstream from site to site. In this case, spatial weights are included to represent the relative effects of tributaries of differing sizes on downstream locations. Covariances may also be 'tail-down,' allowing spatial autocorrelation between sites moving upstream. Tail-up and tail-down covrariances can be flow-connected or flow-disconnected. More practically, tail-up, tail-down, and Euclidean models can be combined in different ways, generating a variety of mixed models. For example, a mixed model that combines all the above models may be written as

$$Y = X\beta + Z_u + Z_d + Z_e + W_k\gamma_k + \cdots + W_p\gamma_p + \varepsilon$$

where X is a designed matrix of fixed effects, β are parameters, Z_u is a random variable with a tail-up autocovariance, Z_d is a random variable with a tail-down autocovariance, Z_e is a random variable with a Euclidean autocovariance, W_k is a designed matrix for random effects γ_k, $k = 1, \ldots, p$, and ε is a measure of error (Ver Hoef *et al.*, 2014).

We used the Spatial Stream Network (SSN) package (Ver Hoef *et al.*, 2014) to fit these geostatistical network models using R statistical software, version 2.14.3 (R Development Core Team, 2012). Because this package requires feature geometry, attribute data, and topological information for stream networks to be stored in a specific manner, we first reprocessed our GIS dataset using an ArcGIS 9.3 toolset, Functional Linkage of Watersheds and Streams (FLoWS, Theobald and Norman, 2005). FLoWS creates aquatic indicators that capture the functional relationship between terrestrial watersheds and streams, building a landscape network (LSN), a graph that stores the topology and geometry of nodes (points where segments intersect), edges (stream segments), and reach catchment areas (RCAs) within the watershed, as well as additional geographic information about the stream system. Using FLoWs, one defines nodes as topologic breaks, including confluences, stream sources, outlet points, and edges as flow paths from node to node in a stream network according to the branching patterns of a stream. In addition, a watershed is defined as the entire land area that contributes water flow to a single stream outlet. Watersheds are composed of a constellation of nonoverlapping but tightly adjacent RCAs that represent the aerial extent that contributes overland flow to a given edge. Matching each edge to its associated RCA allows us to examine the one-to-one functional relationship between them.

We used an additional ArcGIS 9.3 toolset, Spatial Tools for the Analysis of River Systems (STARS; Peterson and Ver Hoef, 2014), to generate data for producing spatial weights. The STARS toolset is used to perform two functions. The first reprocesses the LSN to create a Spatial Stream Network (SSN) object that stores feature geometry, attribute data, and topological information in a way that is effective for fitting spatial models of steam networks in R statistical software (Ver Hoef *et al.*, 2014). The second function creates pre-processing data for calculating spatial weights, including segment proportional influence (PI) and additive function values (AFV). In STARS, stream distance is defined as the shortest distance between two nodes measured along edges. Watershed area is defined as accumulated RCAs downstream from an edge to the outlet node and is computed as the area A^j for an edge. When two edges, denoted by j and j', are connected by a node, the PI for the edge, denoted by ω_j, is the following (Peterson and Ver Hoef, 2014):

$$\omega_j = \frac{A^j}{A^j + A^{j'}}$$

AFV is equal to the product of PI of edges that constitute the downstream path from the jth node to the stream outlet (Peterson and Ver Hoef, 2014):

$$AFV_j = \prod_{k \in D_j} \omega_k$$

We imported values of PI and AFV as well as stream distance into the SSN package to calculate weights for each tributary, denoted as $\pi_{i,j}$, where i refers to a point downstream from point j (Ver Hoef and Peterson, 2013):

$$\pi_{i,j} = \sqrt{\frac{AFV_i}{AFV_j}}$$

For this study, we used the 1 : 24000 stream network for the study area derived from the NHD to define an LSN in FLoWS. Because SWAT subbasins delineation and RCA development using STARS are two separate, nonlinked processes, the centroid of the RCAs were matched to SWAT subbasins and RCAS were then associated with specific subbasins based upon >50% spatial overlap. We then assigned each RCA the watershed-scale variables delineated above for the subbasin to which it corresponded and used this LSN to calculate spatial weights and to fit subsequent SSN models.

We estimated five different geospatial network models to identify relationships between stream flow and the watershed-scale variables in each time-period using SSN, including tail-up, tail-down, Euclidean, and tail-up and tail-down models as well as a mixed tail-up, tail-down, and Euclidean model. This resulted in a total of 25 separate models. We compared the fitted models based on their Akaike Information Criteria (AIC) and several cross validation statistics, including negative two log likelihood (a statistic to compare two models, one of which is nested in another), standard bias, root-mean-square prediction error, root average variance, and confidence interval coverage to select the model for each time period with the best fit.

RESULTS AND DISCUSSION

We analysed the statistical relationships of GIWs and other watershed-scale indicators of hydrologic processes on streamflow, both annually and seasonally. We used a geostatistical modeling method to quantify these relationships and account for spatial dependence due to spatial connectivity, flow volume, and flow direction along stream networks. Employing this methodology was particularly important because exploratory data analysis revealed clear spatial patterns in our streamflow data (Figure 4). Comparisons among the geostatistical model structures suggest that that stream network-based models outperformed the Euclidean model as indicated by lower RMSPE and AIC values (Table II). Of these network models, the mixed model with tail-up and tail-down covariance structures produced the best fit for at least two of the three model objection functions (i.e. the selection criteria; Table II). Thus, we selected this model structure each season and annually to remain consistent across our five final models. Estimates and statistics for the statistically significant variables in these models are summarized in Table III and discussed in the following sections. A table of results for all variables in each model is located in the supporting information.

Geographically isolated wetlands, non–geographically isolated wetlands, and streamflow

Results indicate that two variables related to GIWs are significantly related to streamflow. The first of these, average distance from GIWs in a subbasin, is significantly and positively related to streamflow annually and across all seasons ($p < 0.01$ annually, autumn, winter; $p < 0.05$ spring and summer; Table III). This effect was highest in winter, a dryer period (Table I) with lower potential evapotranspiration rates compared to other seasons. Therefore, winter water storage potential in depressions may be greater than other seasons resulting in a potentially stronger contribution to streamflow (Acreman and Holden, 2013). Effects were similar in spring and autumn and lowest in summer. Results therefore suggest that GIWs distant from streams have greater potential to contribute to streamflow across long time

Table II. Summary statistics for models selection based on AIC, negative two log likelihood (neg2LogL) and root-mean-square prediction error.

	Spring			Summer			Autumn			Winter			Annual		
SSN model	AIC	neg2LogL	RMSPE	AIC	neg2LogL	RMSPE	AIC	neg2LogL	RMSPE	AIC	neg2LogL	RMSPE	AIC	neg2LogL	RMSPE
Tail-up	8888	8870	**839.8**	**8446**	8428	636.8	8647	8629	765.8	8940	8922	993.1	**10 262**	10 244	3364
Tail-down	8897	8879	916.6	8487	8469	698.9	8681	8663	830.4	8979	8961	1091.9	10 300	10 282	3672
Euclidean	8950	8932	935.6	8490	8472	699	8682	8664	831.9	8983	8965	1093.8	10 302	10 284	3679
Tail-up, tail-down, and Euclidean	8889	8847	847.2	8466	8424	635.8	8667	8625	762.4	8959	8917	987.9	10 281	10 239	3348
Tail-up and tail-down	**8877**	**8847**	847.3	8454	**8424**	**634.7**	**8655**	**8625**	**762.4**	**8947**	**8917**	**987.6**	10 269	**10 239**	**3348**

Bold text indicates the best model for each selection criteria.

Table III. Parameter coefficients (Coeff.), standard errors (SE), and *t*-values (*t*) for the statistically significant variables in the final SSN models.

Response variable: streamflow (m^3/s)	Spring				Summer			
Predictor variable	Coeff.	SE	*t*		Coeff.	SE	*t*	
(Intercept)	**−557.25**	112.73	−4.94	***	−49.47	76.57	−0.65	
Wetlands								
All wetland types per subbasin area (NCCREWS) (%)	−2160.78	1759.35	−1.23		**−2582.20**	1216.04	−2.12	*
Depressional swamp forest (GIW; NCCREWS) (%)	**63 830.69**	23 084.54	2.77	*	18 700.81	15 448.74	1.21	
Managed pineland (non-GIW; NCCREWS) (%)	**10 672.51**	4345.99	2.46	*	**7464.60**	2964.81	2.52	*
Emergent herbaceous wetlands (from NLCD 2006) (%)	**24 872.30**	6534.13	3.81	**	**19 633.23**	4523.98	4.34	***
Average distance from GIW to stream (m)	**0.17**	0.08	2.08	*	**0.15**	0.06	2.62	*
Moisture inputs								
Precipitation for time period (mm)	5.12	4.05	1.26		**3.32**	1.15	2.89	*
Runoff indicators								
Hydrologic soil group D (%)	**−32.81**	11.45	−2.86	*	**−20.59**	7.85	−2.62	*
Barren land (rock/sand/clay) (%)	**18 564.66**	4598.73	4.04	***	**13 357.21**	3412.41	3.91	***
Developed, open space (%)	1298.49	3329.48	0.39		**−5029.69**	2338.42	−2.15	*
Mixed forest (%)	608.26	4625.21	0.13		**−8099.54**	3181.59	−2.55	*
Shrub/scrub (%)	−3600.84	3410.25	−1.06		**−5698.03**	2374.27	−2.40	*
Cultivated crops (%)	−2208.21	2278.32	−0.97		**−3813.68**	1609.01	−2.37	*
Pasture/hay (%)	**−5298.64**	2698.20	−1.96	*	**−5687.67**	1835.04	−3.10	**
Open water (%)	3046.05	4186.10	0.73		4343.18	2865.06	1.52	

*$p < 0.05$.
**$p < 0.01$.
***$p < 0.001$.

scales (i.e. seasonally and annually) compared to those GIWs located in closer proximity to streams.

The positive relationship between GIW distance to the stream and streamflow is consistent with studies that suggest water storage areas in the landscape with less persistent watershed-scale connections to a stream (e.g. headwater ponds and wetlands (Daniel, 1981)) – compared to those features more frequently connected (e.g. riparian wetlands, Phillips *et al.,* 2011) – are associated with a greater runoff response following high rainfall periods. A recent meta-analysis further supports this finding, suggesting that wetlands surrounded by uplands can be flood-generating, rather than flood-buffering, areas of the landscape (Acreman and Holden, 2013). We attribute this particular model outcome to two potential processes. First, water transport from distant GIWs to the stream might involve infrequent connections and long transit times for water issuing from GIWs to reach the stream. For example, we found that cumulative average annual streamflow increases concomitantly with the average distance of GIWs to the stream up to an approximately 1000 m distance, after which cumulative streamflow increases at a more rapid rate (Figure 5). Results also suggest that average annual streamflow (noncumulative) increases with average GIW distance to the stream by a power law function ($R^2 = 0.745$, $p < 0.001$). Further, Spearman correlations suggest higher average storage volumes of GIWs with distance from the stream subbasin (a significant, though weak, positive correlation of average subbasin GIW volume with distance of GIW to the stream, $r = 0.15$, $p = 0.0001$) and an increasing density of GIWs with distance to the stream ($r = 0.19$, $p < 0.0001$).

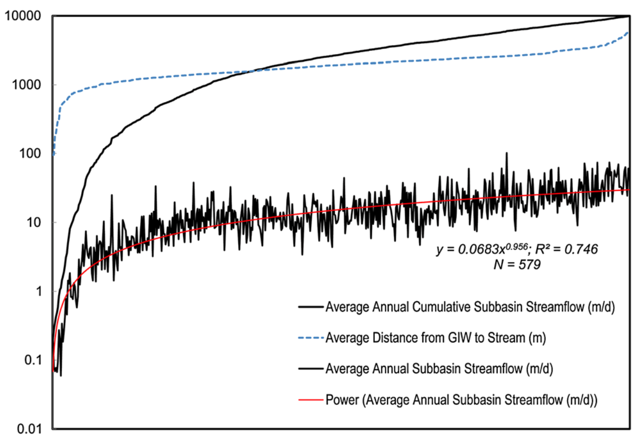

Figure 5. Relationship between cumulative average annual subbasin streamflow and GIW distance to stream and the power law curve showing how subbasin average annual streamflow changes with GIW distance to the stream. Streamflow converted to L/T for comparative purposes.

Autumn			Winter			Annual		
Coeff.	SE	*t*	Coeff.	SE	*t*	Coeff.	SE	*t*
−61.02	92.50	−0.66	−123.26	122.45	−1.01	−263.73	405.49	−0.65
−3189.02	1468.16	−2.17 *	−3672.53	1914.26	−1.92	**−13 715.37**	6428.46	−2.13 *
26 523.35	18 606.14	1.43	34 270.58	24 309.99	1.41	111 695.10	81 421.74	1.37
9777.20	3591.55	2.72 ***	**9868.11**	4636.81	2.13 *	**39 373.40**	15 653.55	2.52 *
21 801.41	5494.70	3.97 **	**35 970.53**	7198.40	5.00 ***	**100 278.80**	24 026.09	4.17 **
0.17	0.07	2.61 **	**0.27**	0.09	3.11 **	**0.79**	0.29	2.69 **
8.62	2.97	2.90 **	−10.06	7.15	−1.41	**7.36**	3.11	2.37 *
−26.96	9.44	−2.86 **	**−38.74**	12.36	−3.13 **	**−115.83**	41.48	−2.79 **
15 349.45	4141.28	3.71 ***	**25 719.01**	5622.32	4.57 ***	**68 811.43**	18 142.57	3.79 ***
−7144.59	2928.06	−2.44 *	−2763.66	3845.88	−0.72	**−27 099.53**	12 560.67	−2.16 *
−9445.75	3765.96	−2.51 *	−8234.23	4955.37	−1.66	**−41 974.72**	16 710.27	−2.51 *
−7214.26	2923.20	−2.47 *	−1410.96	3701.90	−0.38	**−28 998.49**	12 810.36	−2.26 *
−5474.07	2098.77	−2.61 **	−174.95	2900.87	−0.06	**−20 774.77**	8936.19	−2.32 *
−7865.32	2353.53	−3.34 ***	−2748.34	3488.39	−0.79	**−32 067.42**	10 255.09	−3.13 **
4300.96	3585.74	1.20	**13 008.10**	4621.51	2.81 **	22 611.20	15 382.16	1.47

Second, we hypothesize a sequencing of watershed-scale hydrologic connectivity and runoff behavior of water storage and transport features in the landscape, including GIWs, based on our conceptual modeling of connectivity in this watershed. Specifically, following high precipitation periods that occur across all seasons in this watershed (Figure 2), patches of wet areas in the landscape (e.g. variable source areas (Hewlett and Hibbert, 1967) and wetlands) likely begin to hydrologically connect until all parts of the landscape are contributors to streamflow (McDonnell, 2013). By deduction, all parts of the landscape necessarily include GIWs and GIW complexes. In the study of watershed's wetland complexes (Tiner, 2003a), groundwater connections from the wetland to the stream are generally limited because of clayey confining layers underneath sandy loam soils, particularly under historic, nondrained conditions (Sharitz and Gibbons, 1982; Sharitz, 2003). Thus, for GIWs to contribute to streamflow following wet conditions, overflow (i.e. 'spilling') from the wetland and surface and shallow subsurface transport may be important transport processes. However, when the watershed is fully connected hydrologically, depressions that contain substantive volumes of water, such as GIWs, may exhibit a strong contribution to streamflow compared to the surrounding landscape (Ator *et al.,* 2005) and exhibit an effect on the hydrograph. If, however, the mapped GIWs in our study area have been drained for other (e.g. agricultural) purposes (Sharitz, 2003), drainage channels may provide a more direct, rapid route of these water storage areas to the stream following wet events (Acreman and Holden, 2013). Therefore, under wet climatic conditions – that, again, occur across all seasons in the study area – when watershed connectivity, potential connections via drainage channels, and streamflow are high, these distant connections of GIWs could be strong contributors to and result in a positive relationship with streamflow.

The percentage of a subbasin composed of depressional swamp forest GIWs exhibited a positive statistical relationship with streamflow in the spring season only ($p < 0.01$). This GIW type is comprised of nonriverine systems with predominately deciduous species but may also support scrub/shrub communities. These depressional swamp forests typically comprise less than 5% of each subbasin's spatial extent, are evenly distributed across the landscape (data not shown), and have a smaller average areal extent than all wetland types (average area = 0.9 ha and 1.1 ha, respectively). The soils in this wetland type, however, are very poorly drained and exhibit low saturated hydraulic conductivity as well as groundwater exchange and transport from the GIW to the stream (Sharitz, 2003). Water inputs and outputs from these wetlands primarily occur via precipitation and evapotranspiration (Sharitz and Gibbons, 1982), and potentially shallow lateral subsurface flow downgradient toward the stream (Pyzoha *et al.,* 2008). Thus, it is possible that during the spring months, when rainfall is relatively high compared to other periods

(Table I), these poorly drained systems respond rapidly to high precipitation events. This may potentially occur via a fill-spill dynamic similar to that of the bedrock-soil interface (Tromp-van Meerveld and McDonnell, 2006), which thereby creates extensive watershed-scale connectivity. Because of the minimal groundwater transport from these wetlands, water issuing from depressional swamp forests likely occurs via surface and shallow subsurface runoff to other surface waters (McDonnell, 2013). While this hypothesis is grounded in previous work on these systems (Sharitz and Gibbons, 1982; Pyzoha *et al.,* 2008) and potentially generalizable hydrologic processes (McDonnell, 2013), it should be noted that soils surrounding these poorly drained wetlands are often highly permeable sands, and hydrologic and hydraulic connections to downstream surface waters are not well-characterized with currently existing empirical data (Sharitz, 2003).

The percentage of a subbasin that is composed of all wetland (non-GIW and GIW) types was significantly and negatively related to flows during the summer, autumn, and annually ($p < 0.05$), indicating that the cumulative effect of wetlands in a subbasin, including those in floodplain and riparian areas, corresponds to reduced flood flows (Acreman and Holden, 2013) and baseflows during these periods. The results are consistent with studies that indicate the overall attenuating effect of wetlands on flood regimes and baseflow conditions, particularly floodplain and riparian wetlands – those included in our study's 'percent wetlands' predictor variable – that frequently connect and disconnect with stream systems (Sun *et al.,* 2002; Quinton *et al.,* 2003). These findings also align with our study results for other vegetated land covers with high evapotranspiration rates during these seasons (see the following subsection). Summer is a period with high precipitation (Table I) and evapotranspiration (precipitation ~ evapotranspiration) in the Neuse River Basin (Billingsley *et al.,* 1957). Therefore, wetlands in the watershed can retain and store increased quantities of water compared to other seasons because (1) evapotranspiration rates are high thereby affording a consistent capacity for storage as water levels drop because of losses to the atmosphere and (2) there is a steady supply of water to the wetlands from precipitation (Sharitz and Gibbons, 1982) and potential inputs from shallow water table mounding that reflects these high evapotranspiration conditions (Winter and LaBaugh, 2003). This potentially creates a net effect of wetlands as water storage areas in the landscape, which thereby reduces streamflow. In autumn, rainfall is substantially lower compared to summer in the Neuse River Basin (Table I) as is evapotranspiration, as a result of lower temperatures and movement toward the dormant season. Therefore, we posit that the precipitation-evapotranspiration balance of wetlands across the basin during this period also creates the net effect of overall wetland storage and consequent flood attenuation during this period. The annual relationship between streamflows and watershed wetlands is similar but warrants further study for additional insights on these results.

The percentage of a subbasin composed of one non-GIW type derived from the NC-CREWS dataset (managed pineland) dominated this significant, positive impact on streamflow across all seasons ($p < 0.05$; autumn, $p < 0.01$). This relationship decreased from winter to autumn, then summer, and was lowest in spring. Managed pineland in this area is typically bedded, disked, and elevated such that furrows and gullies transport precipitation away quickly following rainfall events (Anderson, 2004). Thus, consistent with our results, these wetlands do not store water and mitigate flooding but rather and more likely contribute to high runoff events. Further, based on NLDC 2006 data, the percent of emergent herbaceous wetlands in the subbasins exhibited a significant and positive relationship with streamflow for each season and annually. These herbaceous wetlands are located close to streams in our study area (100% within a 200 m buffer) and potentially exhibit lower evapotranspiration rates compared to the surrounding landscape and other subbasin wetlands with a higher density of deciduous forests (Sharitz and Gibbons, 1982) – at least during the growing season (late spring, summer, and early autumn in the study area). Combined, the proximity to the stream and comparatively limited evapotranspiration may result in consistent contributions of herbaceous wetland types to streamflow across all seasons.

Watershed hydrologic indicators and streamflow

While this study aims to primarily understand the role of GIWs and other wetlands systems on streamflow, these relationships must be considered in the context of other landscape scale flow-generating or storage mechanisms. Across our study subbasins, precipitation, soil drainage patterns, and specific land cover types were also important factors that explained the variations in streamflow across different seasons and annually. For example, precipitation was significantly and positively related to streamflow in the summer ($p < 0.01$) and autumn ($p < 0.01$) as well as annually ($p < 0.05$) with the strongest influence occurring in the autumn ($\beta = 8.62$), suggesting a positive rainfall-runoff relationship across these periods in the study basin (Table III). Because precipitation and evapotranspiration are approximately equal during the summer and autumn in the study area, this finding may reflect the rapid appearance of convective storm systems in the summer and early autumn in the North Carolina Coastal Plain whereby runoff occurs quickly from wet and ponded areas. Further, precipitation across both seasons is not statistically correlated with average baseflow index (percent of streamflow as baseflow), suggesting that rainfall and runoff events are highly influential on streamflow during these seasons.

The percentage of soils of Hydrologic Soils Group D in a basin was significantly and negatively related to streamflow during all months and annually ($p < 0.01$). While this finding does not correspond to the low infiltration capacity, high runoff potential of this soil category, HSG D soils in this Coastal Plain region could largely reside in small depressional areas with perched water tables that are capable of storing varying volumes of water (Ross, 2003). For example, while variance inflation factors did not reach the >4 threshold when tested, HSG D soils and the percentage of NC CREWS-identified wetlands are significantly correlated ($r = 0.62$, $p < 0.0001$). Thus, these soils can potentially be associated with depressional systems that store water and attenuate streamflow.

The percent land cover composition of a subbasin is significantly related to streamflow for eight of the fourteen land cover types considered in this analysis (for at least one season; Table III). This finding is consistent with numerous studies that have found direct correlations between various land cover types and streamflow (e.g. Endreny, 2005; Schilling *et al.,* 2008; Tu, 2009; Price *et al.,* 2011). Land cover is also one of three primary factors – including soil type and slopes – that governs daily soil water retention in the SWAT model, a parameter in the curve number equation used to estimate daily surface runoff from different combinations of land cover, soil types, and slopes. However, because land cover is only one factor that influences the water balance and runoff in SWAT, any relationship between land cover and simulated runoff is a nonspatial one (i.e. land cover across the watershed is 'lumped' for water balance calculations). Further, our statistical diagnostic tests detected limited correlation among these variables and streamflow; therefore, additional mechanistic explanations for these land cover-streamflow relationships may exist. For example, the percentage of a subbasin composed of barren land significantly and positive influenced streamflow across all months ($p < 0.001$). Barren lands consist largely of bare rock, outcrops, or similar substrates that lack vegetation and soil structure. Moreover, although barren land on average comprises a small portion of the subbasins' land cover (mean = 0.28%; maximum = 16%), these areas are positively correlated with the average subbasin slope ($r = 0.28$, $p < 0.001$). Therefore, these parcels of land are likely to exhibit minimal storage and rapidly transport water off steep areas of the landscape following rainfall, similar to responses of bedrock outcrops (Burns *et al.,* 2001). Thus, all water on these surfaces, whether entering as runoff or precipitation, will typically result in increased streamflow.

The percentage of a subbasin composed of four land cover types was significantly and negatively related to streamflow in the summer and autumn seasons and annually ($p < 0.05$), with the greatest effect in autumn. These included developed open space land cover (which consists largely of vegetation in the form of lawns with less than 20% impervious surfaces), mixed forests, shrub/scrub, and cultivated crops. Similarly, the percentage of pasture and hay in a subbasin had a significant, negative relationship to streamflow in the spring ($p < 0.05$), summer ($p < 0.01$), autumn ($p < 0.001$), and annually ($p < 0.01$) with the greatest impact in the autumn. Results from the spring and summer potentially exhibit growing season dynamics, whereby higher evapotranspiration in these landscapes with various vegetation types may result a negative relationship to streamflow. Autumn and annual results may reflect an interaction between precipitation and evapotranspiration dynamics during these periods that warrants further investigation. The significant and positive relationship of the open water land cover type (i.e. open water with less than 25% vegetation or soil cover) on streamflow during the winter season ($p < 0.01$) may reflect a rapid fill-spill response of these systems during the dormant season.

Model assumptions and sources of uncertainty

This study provides a first step toward understanding the relative contributions of GIWs in the landscape to streamflow; however, some limitations and uncertainties exist. To conduct a geostatistical study across an area this large and within a dense network of subbasins, streamflow estimates are needed. We used the SWAT hydrologic model that predicts streamflow with relatively high accuracy across the subbasins, as suggested by the validation cross-checks at the internal basin gages (see *SWAT watershed delineations and hydrologic simulations*). Drainage areas above the gaged sites are, however, larger than that of this study's subbasins because of the nature of the placement of USGS stream monitoring sites on permanent (nonephemeral, nonintermittent) streams. While this might suggest that streamflow validation is biased toward drainage areas that average two orders of magnitude larger than the largest study subbasin, volumetric streamflow and drainage area in our study area scale linearly (e.g. $R^2 = 0.92$, $p < 0.001$ for average annual streamflow). Therefore, we considered it a reasonable assumption that validation extends to the simulated annual and seasonal streamflows for our study subbasins. Another source of uncertainty is the estimate of GIW distribution and volumetric storage across the study area. While our methods based on previous approaches outlined in the literature (Frohn *et al.,* 2009; Reif *et al.,* 2009); Lane and D'Amico, 2010) and are considered 'best' estimates of the spatial distribution of GIWs, there are currently no existing regional or national maps of GIWs. Also, wetlands in the Carolina bay region, which covers a large portion of the study area, are regularly ditched for agricultural lands uses (Sharitz, 2003; Munoz *et al.*, 2009). This is a metric not available for incorporation into the model but which likely influences connectivity of GIWs to downstream waters. Finally, while the spatial data used in the models are derived from sources with strict quality assurance/quality control measures, a degree of error in spatial databases is to be expected, particularly as all involve aggregating data to a particular grid scale resolution (e.g. 30 m land cover data).

SUMMARY AND CONCLUSIONS

In this paper, we evaluated the significance of GIW characteristics and other landscape indicators of watershed-scale hydrologic processes on simulated streamflow across a dense network of subbasins. We applied a hybrid modeling approach using the SSN geostatistical package in R, which explicitly incorporates spatial covariance in predictor variables with respect to stream networks and connectivity, and the SWAT model, which simulates daily streamflows that are integrated to seasonal and annual time scales.

Our results indicate that GIWs, to some extent, influence streamflow. The farther the GIW from a stream, the greater its capacity to increase streamflow in this study area. Depressional swamp forest GIWs, in particular, were important contributors to streamflow but only in the spring. However, wetlands as a whole in the study area exhibited a flow attenuation capacity across seasons and annually. This is particularly important, as few studies have clearly elucidated this effect. Our study also determined that landscape-scale hydrologic indicators (i.e. watershed characteristics specifically relating to land cover, precipitation, and soil moisture) can, in aggregate with GIWs and non-GIWs, explain variations in seasonal and annual simulated streamflow across a large Coastal Plain watershed. However, while our hypotheses regarding why these relationships may occur are grounded in the literature, the mechanisms of how specific watershed characteristics affect streamflow require further study.

The work described herein substantially advances the science of understanding the watershed-scale effects of GIWs on the downstream hydrograph, particularly in areas – such as this composite of subbasins – with an extensive spatial distribution of GIWs. The approaches we developed and applied are transferrable to other systems, which is particularly important for the future management of GIWs across a variety of physiographic and ecoregions.

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