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Key Points:
- Metrics describing spatial patterns of development were incorporated into spatially-explicit models of water use.
- Spatial patterns of development explained more variability in water use than socio-economic and environmental variables.
- Developed landscapes that promote simple, cohesive, square-like patterns show potential for more efficient use of water.

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Spatial Patterns of Development Drive Water Use

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Abstract Water availability is becoming more uncertain as human populations grow, cities expand into rural regions and the climate changes. In this study, we examine the functional relationship between water use and the spatial patterns of developed land across the rapidly growing region of the southeastern United States. We quantified the spatial pattern of developed land within census tract boundaries, including multiple metrics of density and configuration. Through non-spatial and spatial regression approaches we examined relationships and spatial dependencies between the spatial pattern metrics, socio-economic and environmental variables and two water use variables: a) domestic water use, and b) total development-related water use (a combination of public supply, domestic self-supply and industrial self-supply). Metrics describing the spatial patterns of development had the highest measure of relative importance (accounting for 53% of model's explanatory power), explaining significantly more variance in water use compared to socio-economic or environmental variables commonly used to estimate water use. Integrating metrics characterizing the spatial pattern of development into water use models is likely to increase their utility and could facilitate water-efficient land use planning.

1. Introduction

Effective water planning and management depends on society's capacity to understand how human systems make use of water across space and time. Scientists are increasingly recognizing the spatial configuration and pattern of developed land use as one of the root causes driving spatial variation in water demand (Chang et al., 2010; House-Peters & Chang, 2011; Shandas, 2010; Shandas & Parandvash, 2010). These findings are leading water managers to place an increasing amount of attention on how land use planning could help guide more water efficient development patterns (Gober et al., 2013). Water use modelers, however, have yet to develop a methodology for assessing how the spatial patterns of development influence water use across large geographic regions. Previous research linking water use and land use patterns has focused on relatively small geographic scales such municipalities, neighborhoods and individual cities (Bouziotas et al., 2015; Gober et al., 2013; Shandas, 2010; Shandas & Parandvash, 2010), limiting the ability of water use models to inform regional or landscape-level planning efforts. In this research, we address this limitation by examining the functional relationship between water use and the spatial patterns of development over a large geographical extent.

There is a long history of research studying the effects of the spatial patterns of development (also referred to throughout the literature as urban form) on human and environmental well-being (Anderson et al., 1996; Clifton et al., 2008; Gilbert & Dajani, 1974; Zhao et al., 2010). Broadly defined as the spatial configuration and pattern of human activities at a specific point in time, the concepts of development pattern and urban form have been used for empirical, theoretical and policy-related research (Anderson et al., 1996) across a diversity of disciplines (e.g., landscape ecology, urban planning and geography; Clifton et al., 2008). Despite its use in the broader literature, spatial patterns of development are rarely incorporated into water use models. Water use modelers have measured the type and structure of land uses (e.g., single-family residential, apartments or commercial; Stoker & Rothfeder, 2014) as well as physical features of the built environment (e.g., number of bedrooms and bathrooms, outdoor area, presence of a swimming pool, etc.; Shandas & Parandvash, 2010) to characterize developed areas in relation to water use. Although these studies have

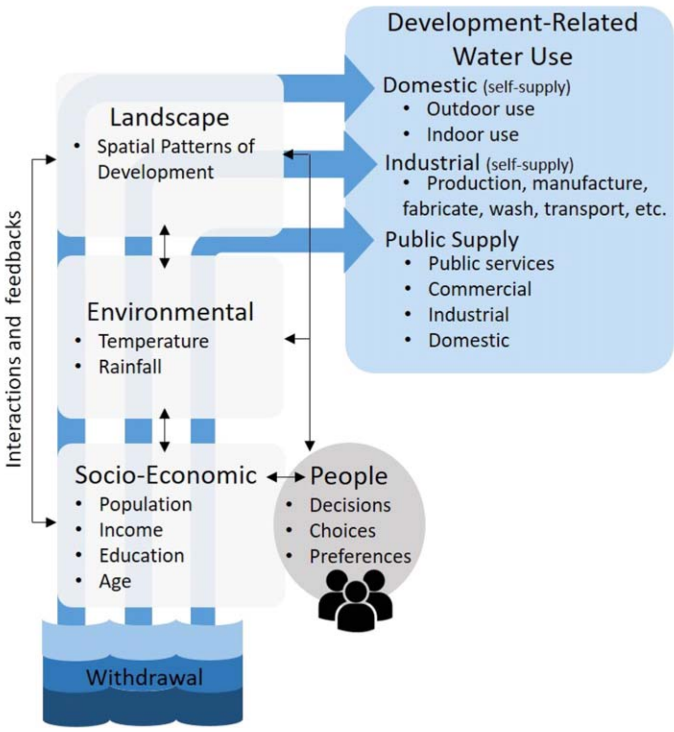

Figure 1. Conceptual framework of development-related water use as a function of land use decisions, socio-economic factors and environmental conditions. The framework depicts a fully coupled human-landscape system considering interactions and feedbacks among determinants of development-related water use (classified as public supply, domestic and industrial categories of use from both public supply deliveries and self-supplied withdrawals).

been able to describe development-related water use, they have utilized methodologies that require high-resolution (i.e., household- or parcel-scale) or site-specific data. These data are often not available at large spatial scales, precluding the use of these methods in analyses covering larger geographic extents. In order to capture regional patterns of development and their associated water demand, the water use modeling community needs focused explorations into metrics that characterize the spatial patterns of development across large geographic extents. Understanding the sensitivity of development-related water use to the spatial patterns of development is a key step in bridging the gap between water use modeling and land use planning.

In this research, we address the functional linkage between water use and the spatial patterns of development, building upon previous research that utilizes physical (e.g., development patterns), socio-economic (e.g., population, education, income, etc.) and environmental factors (e.g., temperature, precipitation, etc.) to explain water use while accounting for spatial heterogeneity in use patterns (Avni et al., 2015; Blackhurst et al., 2010; Franczyk & Chang, 2009; Kontokosta & Jain, 2015; Perrone et al., 2015). Our approach is grounded in the idea that human systems and landscape-scale ecological processes are fully coupled systems (Magliocca, 2008; Werner & McNamara, 2007). Inherent within this idea is the assumption that humans make de facto water decisions as they make land use decisions. Spatially heterogeneous land use decisions, along with exogenous drivers such as climate, result in concomitantly heterogeneous variations in water use. We propose and test a conceptual framework that integrates information on the spatial patterns of development, socio-economic factors and environmental factors as primary drivers affecting the spatial variation of development-related water use (classified as public supply, domestic self-supply and industrial self-supply) (Figure 1).

Through our conceptual framework we evaluate three research hypotheses:

1. Metrics characterizing the spatial patterns of development explain a significant portion of the variance in development-related water use across a mixture of heterogeneous landscapes (significance $p < 0\ .1$). Because land change patterns may not always follow the same trend for residential, industrial and commercial use (Fragkias & Geoghegan, 2010), we test our modeling framework with two water use variables: a) domestic water use (DWU), and b) total development-related water use (TWU; a combination of public supply, domestic self-supply and industrial self-supply).
2. Spatial patterns of development influence water use more than either socio-economic or environmental drivers alone. To test this hypothesis, we construct and compare four model structures (referred to as the Landscape Model, the Socio-economic Model, the Environmental Model and the Holistic Model).
3. Development-related water use may exhibit spatially non-stationary trends. In order to achieve a comprehensive understanding of the variation in water use and to inform how and where water conservation strategies could be implemented, spatial effects need to be incorporated in water use modeling (Franczyk & Chang, 2009; Guhathakurta & Gober, 2007; House-Peters et al., 2010; Wang & Dong, 2017). For example, it is well understood that there is a positive association between air temperature and water use (Balling & Gober, 2007). Consequently, many cities restrict or limit water use for certain activities on excessively hot days. This water management strategy however, may not be optimal given that structural neighborhood characteristics and vegetation make some areas more sensitive to temperature variations (House-Peters & Chang, 2011). By exploring the spatial-nonstationarity of the drivers of water use, our investigation lays the foundation for more targeted, spatially-explicit water management strategies.

To evaluate our hypotheses, we draw inference from two states in the southeastern U.S., North and South Carolina. Both states are experiencing rapid urban growth and expansion with a highly diverse landscape.

In response to the growing recognition that research must ensure reproducibility and accessibility (Cicerone, 2015), we make use of nationally available data sets (i.e., U.S. Geological Survey (USGS) water use records and Census data) as well as open source software (e.g., GRASS GIS, FRAGSTATS and R statistical software) allowing for the replicability of the method.

2. Methods

2.1. Study System

The study system covers the rapidly growing region of North and South Carolina, located in the southeastern U.S. The region is characterized by highly heterogeneous landscapes (Figure 2) and has experienced rapid growth in recent decades. By 2016, the region was home to over 15 million people (U.S. Census Bureau, 2016). The major cities within the region are Charlotte (as of 2017, with over 842,050 inhabitants), Raleigh (458,880 inhabitants) and Greensboro (287,020 inhabitants) all located in North Carolina (U.S. Census Bureau, 2016). Forest land represents the main land use (40%), followed by 18% pasture and cultivated crops, 17% wetlands, 10% developed and residential areas, 7% shrubland, 6% grassland and barren areas and 2% surface water (Homer et al., 2015). The region has experienced more than a 6% increase in developed land cover between 1992 and 2011. The largest proportion of land use change during this period has been caused by deforestation, with 15% of the region's forested land area lost. Excluding total water withdrawals for thermoelectric use, development-related water uses represent the largest water footprint with 25% domestic, 18% public supply (discounting domestic self-supply and industrial-self supply) and 15% industrial water use, according to the 2010 USGS water use records (Maupin et al., 2014). Furthermore, projections of population and economic development suggest that continued growth in the coming decades will place significant pressure on freshwater resources (NOAA, 2013; Sun et al., 2008).

2.2. Scale of Analysis, Data, and Variables

2.2.1. Scale of Analysis

The spatial scale of analysis corresponds to the census tract unit. Census tracts represent a fine-grain scale useful for policy makers and planners (Polebitski & Palmer, 2009). For every variable considered in the

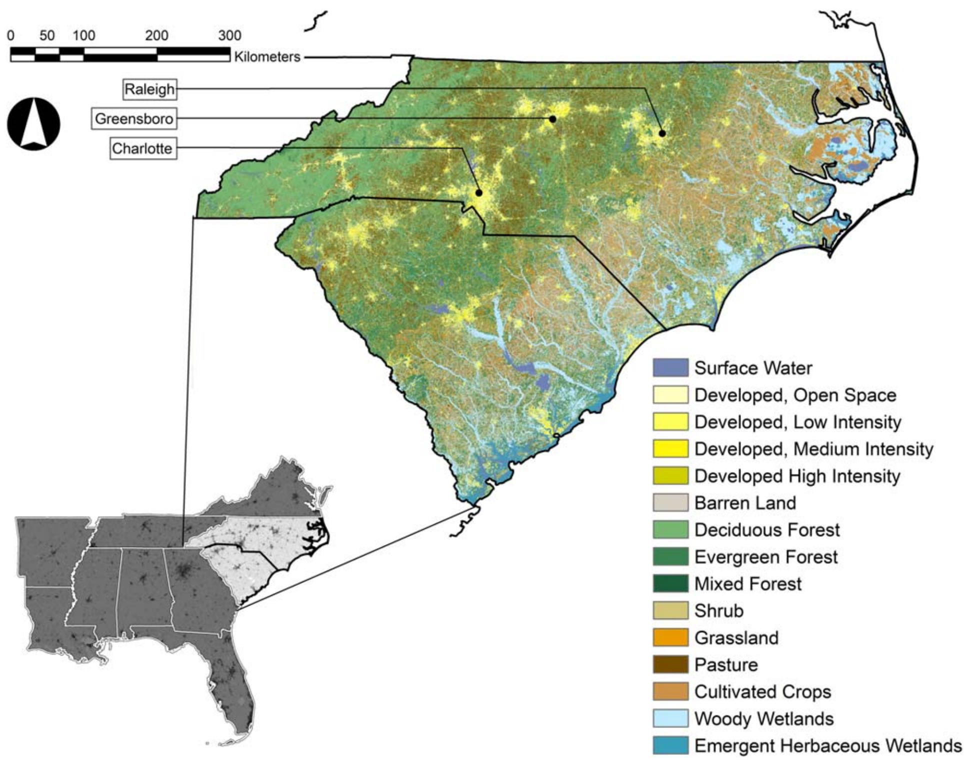

Figure 2. Land cover for the study system as classified by the 2011 National Land Cover Dataset.

modeling framework, we collected the corresponding data set at the census tract or either spatially aggregated or disaggregated the data to fit this unit. Similarly, we conducted all additional data processing steps, such as spatial pattern analysis (see section 2.3), at the scale of the census tract. From the original 3,298 census tracts in North and South Carolina, we identified 40 ‘outliers’ (see section 2.2.2.1), resulting in a sample of 3,258 tracts included in the analysis.

2.2.2. Water Use Records

The USGS National Water-Use Science Project compiles water use information from local, State and Federal agencies on a five-year basis. This data is systematically collected and aggregated at the county, state and national level. Estimates of water use are provided for several categories of use, including public supply, domestic, irrigation, thermoelectric power, industrial, mining, livestock and aquaculture. We obtained estimates of development-related water uses at the county level from the 2010 USGS data set (Maupin et al., 2014). Values of water withdrawal by category of use are presented in millions of gallons per day. For the purposes of this analysis, development-related water use refers to the use volume related to development across the urban-rural gradient and can be categorized as public supply, domestic self-supply and industrial self-supply. Excluded from this analysis are other water use categories such as irrigation for agriculture, thermoelectric, aquaculture, livestock and mining.

2.2.2.1. Spatial Disaggregation of Water Use Records

We conducted a spatial disaggregation technique in which county-level water use records were disaggregated, by class of use, to the census tract unit based on a population-weighted procedure. Through raster algebra, population records at county and census tract scales were used to disaggregate and redistribute DWU and TWU from the coarser (i.e., county) to the finer (i.e., census tracts) scale. Similar underlying procedures are available in the literature, where researchers assume water use to be geographically distributed according to population (Hoekstra & Mekonnen, 2012; Moore et al., 2015). The primary advantage of this technique is that it generates the pycnophylactic property (i.e., volume) which allows a more realistic representation of the underlying water use data. No data are lost or produced during the process and all potential errors are restricted to deviations within each original spatial unit (i.e., county). We examined the disaggregated records (i.e., at the census tract level) of development-related water uses for errors and outliers. This process involved removing un-populated census tracts and areas that presented zero water use values from the analysis. A resulting sample of 3,258 census tracts with corresponding water use records served as the dependent variable for analysis.

2.2.3. Socio-Economic and Environmental Variables

Based on a systematic review of methodological advances in the water demand literature ($n = 30$) we selected eight socio-economic and environmental variables that have been commonly used in previous studies to estimate water use in developed areas. Housing density, education, median age, average household income and an industrial factor (measured as the percentage of individuals employed in water intensive industrial sectors; Table 1) were obtained from the U.S. Census Bureau (2016) at the census tract unit. Annual average temperature and precipitation records over the last 30 years were obtained from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) monthly climate data (PRISM Climate Group, 2004). In order to spatially match temperature and precipitation values from PRISM to the unit of analysis (i.e., census tract), we spatially aggregated from 800 meter grid cells to census tract units. For the last environmental variable, maximum Normalized Difference Vegetation Index (NDVI), we collected 2010 records from the USGS Advanced Very High Resolution Radiometer (AVHRR) data set (https://earthexplorer.usgs.gov/). Similar to the other environmental variables, we spatially aggregated from 1,000 meter grid cells to census tract units to obtain tract-level maximum NDVI records.

2.3. Spatial Pattern Analysis and Landscape Metrics

Across the landscape ecology and urban planning literatures, several metrics have been used to quantify and characterize the spatial pattern of development (Herold et al., 2005; Irwin & Bockstael, 2007; McGarigal et al., 2002; Seto & Fragkias, 2005). We used spatial pattern analysis techniques to quantify different landscape metrics and categorized the spatial patterns of development within the boundaries of each census tract in the study system. We obtained 30 meter land cover data from the 2011 National Land Cover Dataset (NLCD) (Homer et al., 2015) and reclassified the four developed classes (i.e., open space, low intensity, medium intensity and high intensity developed) into one single ‘developed’ class. We included in our analysis areas classified as “open space developed” because they constitute a mixture of impervious surface (less than 20% cover) and vegetation in the form of lawn grasses, and consequently are areas driving demand

Table 1
Summary and Descriptive Statistics of the Socio-Economic and Environmental Explanatory Variables and Water Use Dependent Variables

Independent variable	Description	Min.	Mean	Max.	Std. Dev.
Socio-Economic					
House density	Total number of houses per squared kilometer.	0.41	115.19	1155.00	140.47
Education	Educational attainment, percentage of population 18 years and over with a Bachelor's degree or higher.	1.97	29.46	56.83	9.84
Median Age	Population's median age.	16.50	38.26	67.70	6.96
Household Income	Mean household income (thousands of dollars).	12.22	60.50	325.90	27.05
Industrial	Percentage of civilian employed population 16 years and over in natural resources, construction, maintenance, production, transportation, material moving, agriculture, forestry, fishing hunting and mining occupations.	0.00	27.21	83.19	13.06
Environmental					
Temperature	Average annual temperature from 1980 to 2009 (°C).	9.76	15.91	19.29	1.47
Precipitation	Average annual precipitation from 1980 to 2009 (mm).	930.49	1196.72	2013.92	103.46
Maximum NDVI	Maximum level of photosynthetic activity in the canopy during growing season.	0.00	170.30	245.78	14.59
Dependent variable					
Water Use					
Domestic Water Use (DWU)	Total domestic water use from public supply deliveries and self-supplied withdrawals in millions of gallons a day.	0.01	0.34	1.90	0.16
Total Development-related Water Use (TWU)	A combination of public supply, domestic self-supply and industrial self-supply in millions of gallons a day.	0.01	0.81	23.21	1.05

Note. Values are by census tract.

for domestic outdoor water use. We carried out all measures of landscape metrics using the spatial pattern analysis software FRAGSTATS (McGarigal et al., 2002), the most widely used software in research exploring landscape-level ecological issues (Wang et al., 2014). Due to the novelty of this approach, we conducted an exploratory analysis on multiple landscape metrics to identify the ones that best relate to the spatial variation in development-related water use across the heterogeneous mixture of development densities that shape the study system. We computed twelve class-level pattern metrics and considered all metrics for a single class 'developed', where the spatial arrangement of all developed land patches in a given census tract was measured for each census tract. These pattern metrics included: the Number of Patches; the Patch Density; the Largest Patch Index; the Edge Density; the Landscape Shape Index; the Fractal Dimension Index; the Perimeter-Area Ratio; the Patch Cohesion Index; the Nearest-Neighbor Distance; the Shape Index; the Aggregation Index; and the Clumpiness Index. We constructed a correlation matrix to explore the linear relationship between each landscape metric in relation to one another, to other independent variables, to population estimates and to DWU and TWU. We excluded correlated metrics (linear relationships > 0.5) from the analysis to prevent multicollinearity and kept only metrics that explained a significant portion of variance in the DWU and TWU models.

2.4. Water Use Modeling Framework

We examined landscape patterns, socio-economic and environmental determinants of water use by implementing two modeling methods. The first technique, global regression or multiple linear regression, allows for an examination of the significance and effect size of individual determinants that influence DWU and TWU. This analytical approach makes use of all the observations at all locations to fit one single regression model. Multiple linear regression has been widely implemented across the water demand literature (Arbues et al., 2010; Shandas & Parandvash, 2010; Wentz & Gober, 2007). The second technique, Geographically Weighted Regression (GWR), improves our understanding of micro or neighborhood effects by capturing local spatial variation in DWU and TWU. GWR is similar to multiple regression but introduces complexity

Table 2
Summary and Descriptive Statistics on Landscape Metrics

Metric	Description	Value range	Min.	Mean	Max.	Std. Dev.
Shape Index (SI)	Area-weighted Mean Shape Index. Normalized ratio of patch perimeter to area in which the complexity of patch shape is compared to a standard shape (square) of the same size.	$1 \leq SI < $ No limit. The index equals 1 for square patches of any size and increases as patches become more geometrically complex.	1.00	7.23	27.92	4.08
Aggregation Index (AI)	The ratio of the observed number of like adjacencies to the maximum possible number of like adjacencies given the proportion of the landscape composed of each patch type.	$0 \leq AI \leq 100$. The index equals 0% when patches are maximally disaggregated and 100% when patches are maximally aggregated.	1.32	80.16	100.00	15.76

Note. Values are by census tract.

into the model by integrating the geographic coordinate of each observation, allowing different relationships to exist at different locations (Brunsdon et al., 1996). The process estimates a regression equation for each location from a subset of nearby observations, allowing spatial dependencies to vary from neighborhood to neighborhood. Coefficients and intercept estimates are subjected to weighted values of neighboring observations, commonly defined by a distance-decay kernel function. In other words, it is assumed that points located further from a given location are more likely to present differing coefficients than points that are located closer (Fotheringham & Brunsdon, 1998). We carried out all GWR analysis with the "spgwr" package for R statistical software (Bivand & Yu, 2017). Due to the varied density of census tract centroids (i.e., highly populated city centers present a clustered distribution of tracts while rural areas present a dispersed distribution) we conducted an adaptive Gaussian kernel approach to properly sample nearby observations and capture similar numbers of observations across the rural and urban contexts. In order to optimize the neighborhood size we calibrated the bandwidth by minimizing a cross-validation score (Brunsdon et al., 1996).

We constructed and compared four models with different structures (referred to as the Landscape Model, the Socio-economic Model, the Environmental Model and the Holistic Model) to examine the independent and collective utility of the different landscape pattern, socio-economic and environmental variables for explaining variation in DWU and TWU. To develop the Landscape Model, we evaluated the ability of multiple landscape metrics (the Number of Patches, the Patch Density, the Largest Patch Index, the Edge Density, the Landscape Shape Index, the Fractal Dimension Index, the Perimeter-Area Ratio, the Patch Cohesion Index, the Nearest-Neighbor Distance, the Shape Index, the Aggregation Index and the Clumpiness Index) to explain a significant portion of the variance in DWU and TWU. In order to construct the Socio-economic Model and Environmental Model) we incorporated variables that had been widely implemented across the literature to estimate and project water demand for development-related water uses (House-Peters & Chang, 2011). Finally, we constructed a Holistic Model by combining landscape pattern, socio-economic and environmental variables to test the ability of this combined structure to improve model performance, while still maintaining parsimony. To further investigate how the landscape metrics and the other independent variables influence water use we conducted an assessment of relative importance based on the Lindeman, Merenda and Gold method (LMG) (Grömping, 2007). This approach allows us to compare the explanatory power of each independent variable in the global Holistic models.

We developed all the models in the same fashion, through an iterative process of adding and subtracting variables to improve model performance (see section 2.5). No linear relationship between any pair of variables was greater than 0.5 and the variance inflation factor (VIF) was calculated for every model to check for multicollinearity (Lin et al., 2011). We provide a summary and descriptive statistics for all the independent variables incorporated into the models (Tables 1 and 2).

2.5. Assessing Model Performance and Spatial Heterogeneity

To investigate the importance of the spatial component and test for spatial non-stationarity we compared the global regression model to the GWR model using the adjusted R-squared, quasi-global R-squared and Akaike Information Criterion (AIC). A model with relatively large adjusted R-squared and small AIC values indicates more predictive power and would be preferable. Additionally, both adjusted R-squared and AIC allow comparison between models with different numbers of explanatory variables as they penalize for the number of terms added to a model. We used the variation of coefficients generated by the GWR models to explore spatial non-stationary relationships between variables (Brunsdon et al., 1998). As described by Fotheringham et al. (2002) the range of local parameter estimates can be compared to the confidence interval of global parameter estimates to examine the degree of spatial non-stationarity. Fotheringham et al. (2002) suggest that spatial non-stationarity is present if the inter-quartile range of a GWR coefficient is greater than two times the standard error of the global regression. Lastly, to further test for spatial non-stationarity, we conducted a Monte Carlo significance test (Brunsdon et al., 1996). This technique tests the null hypothesis that estimated coefficients do not vary from one location to another for any given independent variable. In other words, if the GWR models were to be calibrated with observations of dependent and independent variables randomly distributed across space, little to no difference in the pattern of estimated coefficients would be detected. To conduct the Monte Carlo test we used the 'GWmodel' package for R statistical software (Gollini et al., 2015).

3. Results

3.1. Exploratory Analysis on Landscape Metrics

Through the correlation matrix we identified metrics with strong correlation to DWU and TWU and excluded metrics that introduced collinearity issues. The Shape Index, a measure of patch geometric complexity and the Aggregation Index, a measure of aggregation of developed patch mosaic (Table 2) exhibited the most significant associations with variations in development-related water use (Tables 3 and 4). Overall, our inspection of the spatial distribution of landscape metrics across the study system revealed that densely urbanized census tracts present lower values of the Shape Index and high values of the Aggregation Index while in tracts closer to rural areas (low developed density) the Shape Index values increase and the Aggregation index values decrease (Figure 3). Furthermore, the relationship between complexity and aggregation of the developed patch mosaic is not linear, instead it described a graphical shape that assimilates a parabola where suburban and rural census tracts present more varied combination of landscape metrics than densely urbanized census tracts (Figure 4).

3.2. Global-to-Local Regression Models of Water Use

For the global regression model, the Holistic Model performed the best, explaining 22% of the DWU (Table 3) and 19% of the TWU variation (Table 4). Of the reduced models, the Landscape Models explained more variance in the water use data (10% of DWU and 7% of TWU) than the Socio-economic (6% of DWU and 4% of TWU) and the Environmental Models (5% of DWU and 8% of TWU). The Shape Index showed the highest relative importance in the global Holistic models, accounting for 53% of the global DWU model's explanatory power (Figure 5a) and 40% of TWU (Figure 5b). Temperature was the second strongest predictor, with a relative importance of 20% in the DWU (Figure 5a) model and 42% in the TWU model (Figure 5b). These are strong indications that incorporating information regarding the spatial pattern of development into the modeling framework can improve development-related water use estimates at the census tract level of analysis. The Aggregation Index only showed a relative importance of 3% in relation to DWU, and did not significantly explain TWU variance in the Holistic global regression model.

Across all models, GWR outperformed global regression as indicated by lower AIC values and higher quasi-global R-squared values (Tables 3 and 4). The GWR Holistic Model structure exhibited the best model performance, explaining on average 44% of the variation in DWU and 45% in TWU. The important improvement in model performance from global regressions to GWR models indicates spatial non-stationarity in statistical relationships across the study region. Section 3.3 provides an in-depth analysis of spatial heterogeneity as represented by the GWR models. The spatial distribution of local R-squared values for each census tract ranged from 0.17 to 0.65 for DWU (Figure 6a) and from 0.14 to 0.60 for TWU (Figure 6b). Standard error values for census tracts ranged from 0.00 to 0.11 for DWU (Figure 6c) and from 0.00 to 0.47 for TWU (Figure 6d). Mainly based on the small standard errors, DWU was slightly better represented by the corresponding Holistic GWR model than TWU. Overall, the Holistic GWR model explained variation in both DWU and TWU well across a wide range of urban and rural landscapes, displaying similar patterns in local R-squared values (Figure 6).

Table 3
Parameters and Statistics for Domestic Water Use (DWU) Global Regression and Geographically Weighted Regression Models

		Global regression		Geographically weighted regression				
		Coef.	S.E.	Min.	First Qu.	Median	Third Qu.	Max.
Landscape Model	Intercept***	0.16	0.02	−2.92	−0.01	0.10	0.18	0.45
	Shape Index***	0.01	0.00	0.01	0.01	0.02	0.03	0.08
	Aggregation Index***	0.00	0.00	−0.00	0.00	0.00	0.00	0.03
	AIC	−3237		−4099				
	Adjusted R-squared	0.11						
	Quasi-global R-squared			0.34				
Socio-economic Model	Intercept***	0.48	0.02	−0.08	0.36	0.46	0.57	0.86
	Education***	0.00	0.00	−0.00	0.00	0.00	0.00	0.01
	Median Age***	−0.01	0.00	−0.01	−0.01	−0.01	−0.00	0.00
	Household Income***	0.00	0.00	−0.00	0.00	0.00	0.00	0.00
	House Density***	−0.02	0.00	−0.05	−0.02	−0.02	−0.01	0.03
	AIC	−3070		−3772				
	Adjusted R-squared	0.06						
	Quasi-global R-squared			0.28				
Environmental Model	Intercept***	−0.21	0.06	−38.13	−1.43	−0.41	0.48	18.77
	Temperature***	0.03	0.00	−0.90	−0.04	0.01	0.05	2.20
	Precipitation	0.00	0.00	−0.01	0.00	0.00	0.00	0.01
	Maximum NDVI***	0.00	0.00	−0.00	0.00	0.00	0.00	0.01
	AIC	−3033		−3622				
	Adjusted R-squared	0.05						
	Quasi-global R-squared			0.23				
Holistic Model	Intercept**	−0.16	0.06	−15.45	−0.97	−0.21	0.24	5.44
	Median Age***	−0.01	0.00	−0.01	−0.01	−0.01	−0.00	0.00
	Household Income***	0.00	0.00	−0.00	0.00	0.00	0.00	0.00
	Temperature***	0.03	0.00	−0.33	−0.01	0.02	0.05	0.92
	Maximum NDVI***	0.00	0.00	−0.01	0.00	0.00	0.00	0.01
	Shape Index***	0.02	0.00	0.01	0.01	0.02	0.02	0.08
	Aggregation Index**	0.00	0.00	−0.00	0.00	0.00	0.00	0.03
	AIC	−3659		−4494				
	Adjusted R-squared	0.22						
	Quasi-global R-squared			0.44				

Note. *significance $p < 0.1$, **significance $p < 0.01$, ***significance $p < 0.001$, Coef. = coefficient, S.E. = standard error, Min. = minimum, Qu. = quartile, Max. = maximum, AIC = Akaike Information Criterion. Coefficients are not standardized.

Performance of the Holistic GWR model for DWU (local R-squared ranged from 0.17 to 0.65) and TWU (local R-squared ranged from 0.19 to 0.60) varied across the urban corridor that extends along Interstate 85 from Durham, NC, to Anderson, SC (Figure 6). Overall, both models performed well across rural and urban coastal communities such as the Albemarle-Pamlico Peninsula, NC, and the city of Charleston, SC. We found that the largest continuous area with relatively low model performance (R-squared ≤ 0.20) was located in the city and suburbs of Florence, SC. The majority of the other areas that show model underperformance correspond to protected areas such as Great Smoky Mountains National Park, the Savannah River Site nuclear complex and the Fort Bragg Military Reservation. Finally, small areas such as the Raleigh-Durham International Airport, NC, represent another example of locations that displayed low model performance.

3.3. Representing Spatial Heterogeneity

GWR coefficients varied considerably between census tracts for each model structure (Tables 3 and 4). Inter-quartile ranges of coefficient values were greater than two times the standard error of the global regression coefficient (Brunsdon et al., 1998; Fotheringham et al., 2002), indicating potential spatial non-stationarity in every variable. The Monte Carlo significance test for spatial non-stationarity corroborated that temperature, maximum NDVI and the Shape Index vary significantly over space for both DWU and TWU

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Table 4
Parameters and Statistics for Total Development-Related Water Use (TWU) Global Regression and Geographically Weighted Regression Models

		Global regression		Geographically weighted regression				
		Coef.	S.E.	Min.	First Qu.	Median	Third Qu.	Max.
Landscape Model	Intercept***	12.93	0.08	2.21	12.25	12.68	13.10	15.21
	Shape Index***	0.05	0.00	−0.03	0.04	0.06	0.08	0.29
	Aggregation Index	0.00	0.00	−0.02	−0.00	0.00	0.01	0.11
	AIC	6512		5358				
	Adjusted R-squared	0.07						
	Quasi-global R-squared			0.37				
Socio-economic Model	Intercept***	13.73	0.09	12.54	13.37	13.73	14.20	15.60
	Education***	0.01	0.00	−0.03	−0.01	−0.00	0.01	0.03
	Median Age***	−0.01	0.00	−0.05	−0.02	−0.01	−0.01	0.03
	Industrial	−0.00	0.00	−0.02	−0.00	0.00	0.01	0.03
	House density***	−0.07	0.01	−0.26	−0.10	−0.07	−0.03	0.06
	AIC	6613		5457				
	Adjusted R-squared	0.05						
	Quasi-global R-squared			0.37				
Environmental Model	Intercept***	10.26	0.25	−93.25	3.35	7.79	12.86	99.27
	Temperature***	0.14	0.01	−4.31	−0.22	0.14	0.40	6.00
	Precipitation	0.00	0.00	−0.01	−0.00	0.00	0.00	0.07
	Maximum NDVI***	0.01	0.00	−0.02	0.00	0.01	0.02	0.05
	AIC	6475		5485				
	Adjusted R-squared	0.09						
	Quasi-global R-squared			0.35				
Holistic Model	Intercept***	10.66	0.21	−28.07	6.87	9.85	13.69	61.06
	Median Age***	−0.02	0.00	−0.04	−0.02	−0.02	−0.01	0.02
	Education*	0.00	0.00	−0.02	−0.01	−0.00	0.00	0.02
	Temperature***	0.14	0.01	−2.54	−0.09	0.13	0.34	2.52
	Maximum NDVI***	0.00	0.00	−0.03	0.00	0.01	0.01	0.04
	Shape Index***	0.05	0.00	−0.00	0.04	0.05	0.08	0.13
	AIC	6099		5026				
	Adjusted R-squared	0.19						
	Quasi-global R-squared			0.45				

Note. *significance $p < 0.1$, **significance $p < 0.01$, ***significance $p < 0.001$, Coef. = coefficient, S.E. = standard error, Min. = minimum, Qu. = quartile, Max. = maximum, AIC = Akaike Information Criterion. Coefficients are not standardized.

and Aggregation Index for DWU (Table 5). Spatial non-stationarity in median age, household income and education did not exist for DWU nor TWU (Table 5).

Overall, increases in the geometric complexity of spatial patterns of development (measured by the Shape Index) was associated with higher water use of DWU and TWU (Figures 7 and 8). In contrast, DWU regression coefficients of the Aggregation Index varied in magnitude and direction across space (Figure 7). For DWU, the distribution of coefficients (Figure 9, y-axis) relative to development density (Figure 9, x-axis) showed that the Aggregation Index coefficient values are large and positive in highly urbanized census tracts but smaller and more variable in sign in rural census tracts.

4. Discussion

A lack of understanding about how the spatial pattern of development affects the variation in water use can hinder the development of water efficient planning guidelines. Through a coupled human-landscape systems lens we established the functional link between land use decisions, socio-economic factors and environmental conditions (Figure 1). Our results indicate that incorporating spatial configuration into both non-spatial and spatial modeling techniques better explains the sensitivity of water uses to development patterns after accounting for frequently-used socio-economic and environmental variables. Measures of

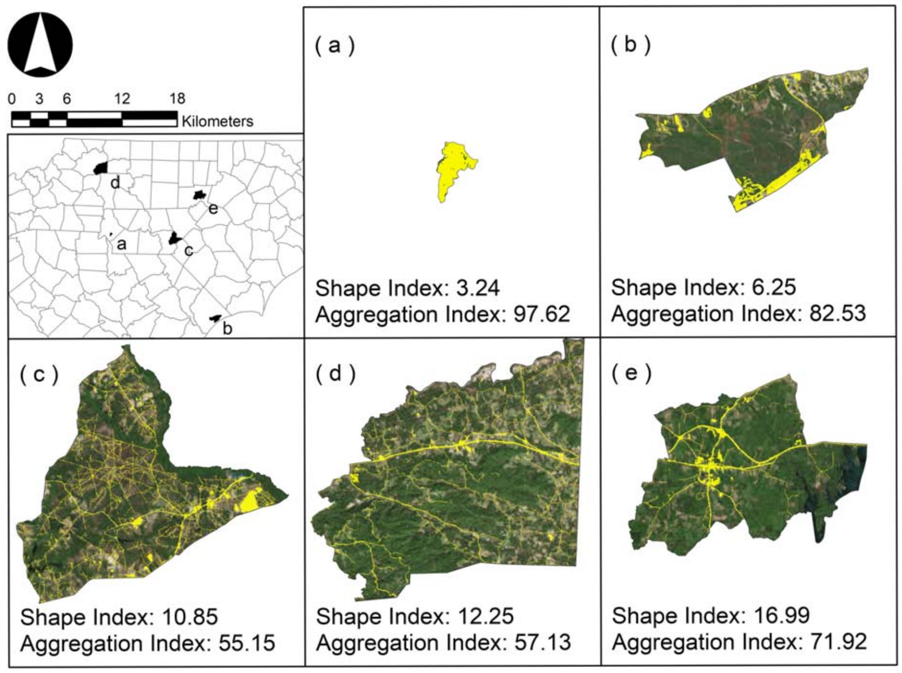

Figure 3. Landscape metrics of sampled census tracts across the study region, located in the southeastern U.S. Randomly sampled tracts described a spectrum of spatial patterns characterizing city centers ((a) Charlotte, NC), urban ((b) Myrtle Beach, SC), suburban ((c) Hoffman, NC) and rural areas ((d) Wilkesboro, NC and (e) Pittsboro, NC). For visual purposes, we overlaid the 2011 NLCD developed cover (bright yellow) on top of aerial imagery maps to highlight the measured patches within each census tract.

development patterns have commonly relied on high resolution or parcel-level data sets limiting replicability and scalability (e.g., Chang et al., 2010; Shandas & Parandvash, 2010; Stoker & Rothfeder, 2014). To overcome these challenges, we proposed and tested a novel implementation of spatial pattern analysis to quantitatively measure landscape metrics that allow characterizing the spatial pattern of development at a large scale (Figure 4). Our approach made use of nationally available data sets and open source software to ensure reproducibility, and our analysis was conducted at the census tract level to provide locally meaningful results across the heterogeneous region of North and South Carolina.

4.1. Effects of the Spatial Pattern of Development on Water Use

The spatial pattern of development is a result of the socio-economic, environmental and political factors that interact in a given location (Medda et al., 1998) and ultimately impact human behavior. In this analysis we demonstrated that the different spatial patterns that shape the built environment of communities across the study system have a strong effect on the way their inhabitants use water for domestic, industrial and public supply needs. We concluded that out of twelve evaluated landscape metrics, the Shape Index (complexity of the developed patch mosaic) and the Aggregation Index (dispersion of developed patch mosaic) were the metrics that best explained variations in water use throughout the urban-rural gradient. In relation to both DWU and TWU, we failed to reject our first research hypothesis, that the spatial patterns of development explain a significant portion of the variance in development-related water use across a mixture of heterogeneous landscapes (Tables 3 and 4). These findings contribute to the growing body of knowledge studying the effects of the spatial pattern of development on human and environmental well-being, such as connections to open space availability, traffic flow, physical activity, thermal efficiency, greenhouse gas emissions, ecosystem services, sustainability and water use (Alberti, 2005, 2007; Boarnet & Crane, 2001; Frank et al., 2005; Shandas & Parandvash, 2010; Stone & Rodgers, 2001; Tratalos et al., 2007; Zhao et al., 2010).

To date, water conservation guidelines directed to inform future development patterns have mainly focused on the distribution and size of housing units and population density (Chang et al., 2010; Shandas & Parandvash, 2010; Stoker & Rothfeder, 2014). For example, Shandas and Parandvash (2010) found that

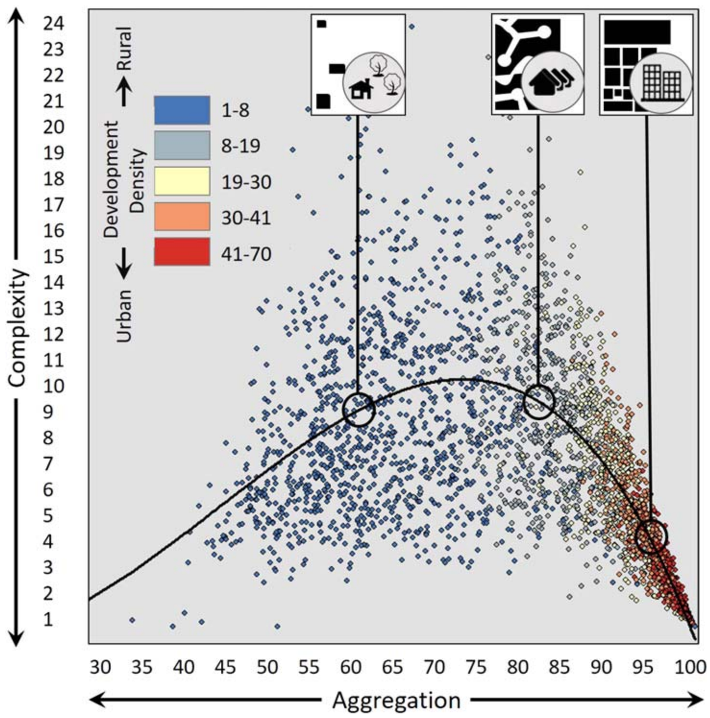

Figure 4. Distribution of complexity (measured by the Shape Index) by aggregation (measured by the Aggregation Index) of the developed patch mosaic for the 3,258 evaluated census tracts across North and South Carolina. For clarity, each census tract is colored-coded within a development density gradient and examples of specific landscapes characterized by the landscape metrics are provided.

decreasing the area of single-family residential units by 100 m^2 could reduce water demand by 978,000 gallons a year for Portland, Oregon. By introducing landscape metrics into a spatially-explicit water use modeling framework we achieved a locally meaningful understanding of the relationship between development patterns and water use at a large scale. These outcomes are important to gain targeted insights into how land use planning could help guide future growth towards urban settlements that make more efficient use of freshwater resources. For example, land and water managers throughout the study system can now situate future development projects along a 'Complexity by Aggregation' distribution and have a better understanding of relative water use requirements that individual development projects will have. This research provides a tool to understand the impact in regional water demand of continuing a trajectory of growth dominated by the irregular and fragmented landscapes of urban sprawl (Feng & Li, 2012). A spatial pattern that can be associated with higher demand for both indoor and outdoor domestic water use as larger residential units and higher presence of amenities such as lawns and swimming pools provide more opportunities to use more water (Harlan et al., 2009). On the other hand, a trajectory of growth directed to develop vacant parcels nearby previously built areas (also known in the literature as infill development, Paulsen, 2013) and incentivize smaller housing units could result in lower domestic water use overall.

4.2. A Holistic Understanding of Water Use

By comparing different water use drivers in independent model structures (referred to as the Landscape Model, the Socio-economic Model and the Environmental Model) we defined the types of drivers that affect demand the most. In relation to our second research hypothesis, we found that the spatial patterns of development influence DWU more than the socio-economic or environmental drivers. We also found contrasting results in relation to TWU based on the regression technique used. The better performance of the Landscape Models when fit to DWU data, as opposed to TWU data, is likely due to the predominance of residential land. Development for residential use represents the main driver of land conversion across the region and projections show this trend to continue (Terando et al., 2014).

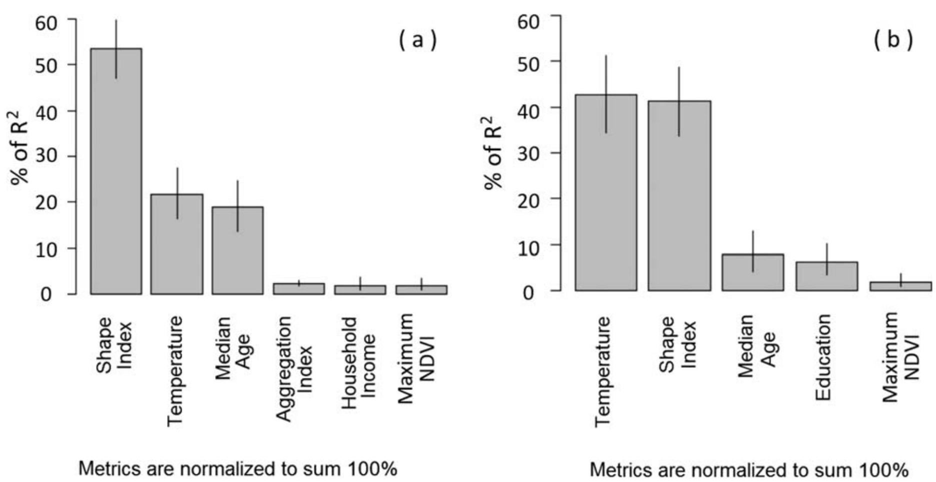

Figure 5. Measures of relative importance for Global Regression predictors of (a) domestic water use (DWU) and (b) total development-related water use (TWU) with a 95% bootstrap confidence intervals. Method LMG.

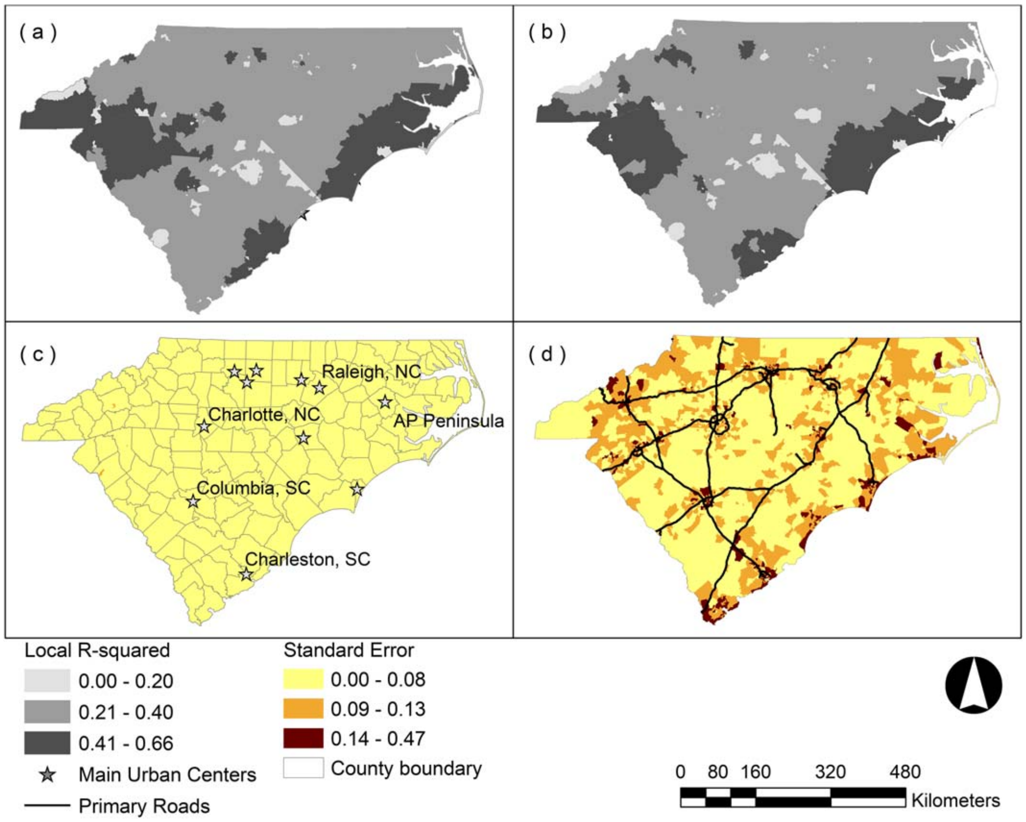

Figure 6. Geographically weighted regression spatial distribution of (a) domestic water use (DWU) local R-squared, (b) total development-related water use (TWU) local R-squared, (c) DWU standard error and (d) TWU standard error.

Incorporating metrics that describe the spatial patterns of development along with indicators of socio-economic and environmental conditions improved model performance and provided a more holistic understanding of variations in water use. We concluded that the Holistic GWR model – integrating median age, household income, temperature, NDVI, the Shape Index and the Aggregation Index – best explained DWU. For TWU, however, including the Aggregation Index did not improve model performance. This is likely due to different mechanisms of water demand for industrial and commercial land use. Land conversion for commercial or industrial development is commonly assumed to occur as a result of profit maximization, government or neighborhood regulations and environmental amenities (Fragkias & Geoghegan, 2010). While several theories describe how and where this process happens, employment decentralization has been described as the dominant trend in the U.S., predominantly for manufacturing facilities (Glaeser & Kahn, 2001). Patterns of dispersed industrial and commercial land use contrast with the various degrees of residential land consumption that characterize the region, which in turn might explain why the Aggregation Index is not a robust driver for explaining TWU as it incorporates industrial and commercial categories of use.

Table 5
Monte Carlo Significance Test for Spatial Nonstationarity

Model	Predictors	p-value
GWR Holistic for DWU	Intercept	<0.01
	Median Age	0.64
	Household Income	0.10
	Temperature	<0.01
	Maximum NDVI	0.08
	Shape Index	0.01
	Aggregation Index	0.01
GWR Holistic for TWU	Intercept	<0.01
	Median Age	0.99
	Education	0.79
	Temperature	<0.01
	Maximum NDVI	0.03
	Shape Index	<0.01

Note. DWU = domestic water use, TWU = total development-related water use, GWR = geographically weighted regression.

Socio-economic variables such as education, age and income have a long history of use, particularly in econometric water use models directed to draw policy and pricing recommendations for domestic water use (Arbues & Villanua, 2006; Foster & Beattie, 1979; Martinez-Espineira, 2002). In our study, education, age and income also significantly explained a portion of DWU and/or TWU variance, but with

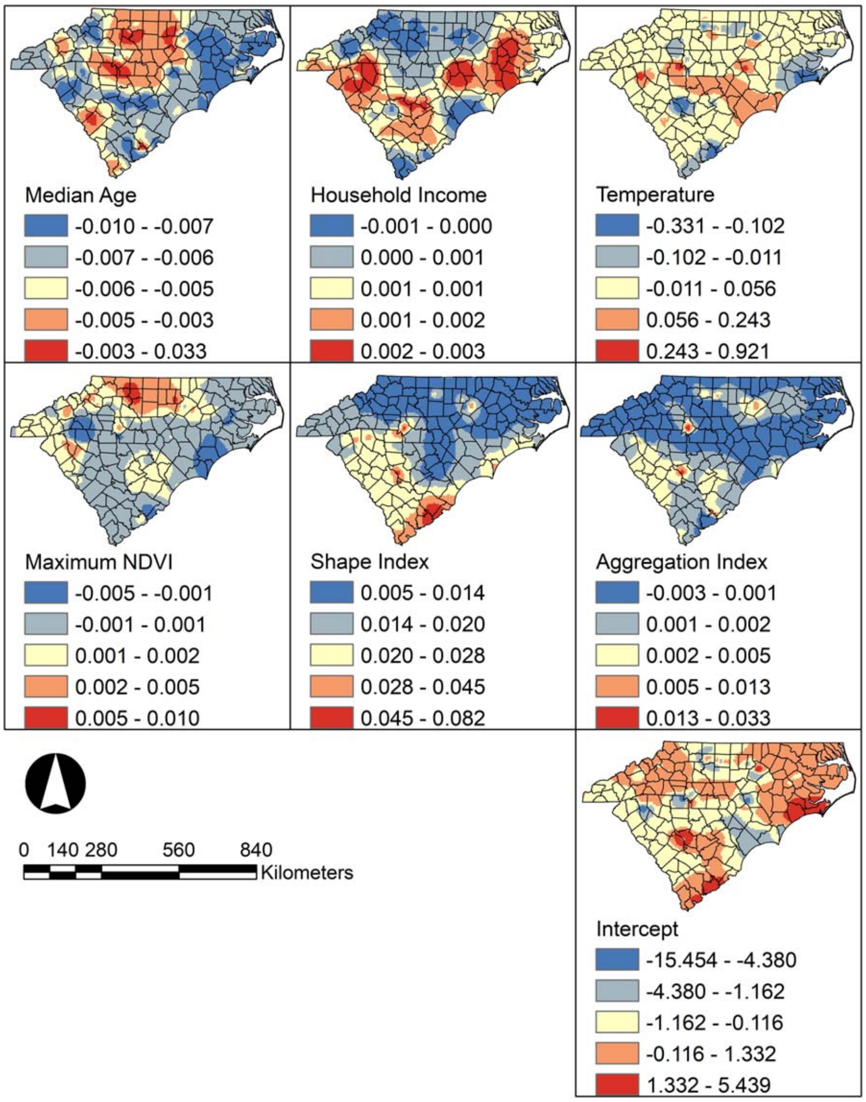

Figure 7. Spatial distribution of the domestic water use (DWU) geographically weighted regression coefficients. Higher coefficients indicate a greater relationship between explanatory variables and DWU.

relatively lower explanatory power ($<$ 18%, Figure 5) compared to the physical environment and spatial patterns of development. The use of vegetation and temperature variables have important applications in explaining domestic outdoor water use (Breyer et al., 2012; Guhathakurta & Gober, 2007, 2010). We found the environmental variables explained an important portion of water use across the study system (accounting for 20% of the DWU and 40% of the TWU model's explanatory power, Figure 5). The addition of landscape metrics is a novel application in water use studies. Through our analysis, we were able to corroborate previous studies that showed a correlation between land and water use (Chang et al., 2010; Shandas & Parandvash, 2010; Stoker & Rothfeder, 2014). We found that landscape metrics accounted for up to 55% of the Holistic DWU model's explanatory power and up to 40% for the TWU model (Figure 5).

The models revealed a surprising inability to explain water use at some locations, such as Florence, SC (local R-squared $\leq$ 0.20). The region surrounding Florence has intense agriculture and pasture activities with small towns scattered throughout, which may be associated with low regulation on private self-supply wells and underestimates of development-related water use. The Raleigh-Durham International Airport, NC, represents another interesting example. The large extension of impervious cover that shapes the airport and extends across most of the census tract could be comparable to a large continuous area of developed land that characterizes a city center. However, the median age, education and household income covariates that

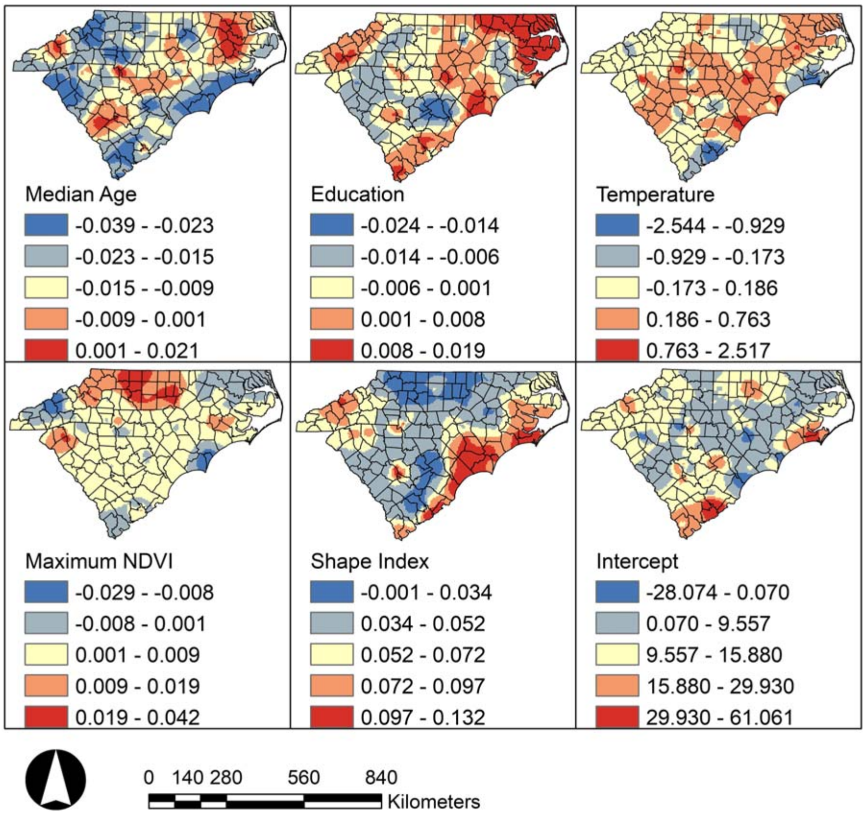

Figure 8. Spatial distribution of the total development-related water use (TWU) geographically weighted regression coefficients. Higher coefficients indicate a greater relationship between explanatory variables and TWU.

help to explain water use in the models are close to zero for this census tract, causing the model to underperform. Similarly, protected land such as Great Smoky Mountains National Park, the Savannah River Site nuclear complex and the Fort Bragg Military Reservation showed model underperformance likely due to the specific nature of low population, low development or un-reported use. Overall, model performance declined in areas with very low population levels; this pattern is likely associated with instability in the spatially disaggregated estimates in areas with low population and inherently large census tracts. Our work suggests a need to standardize public water use records at finer grain spatial resolutions in order to better estimate and project water demand across the conterminous U.S. (Pickard et al., 2017).

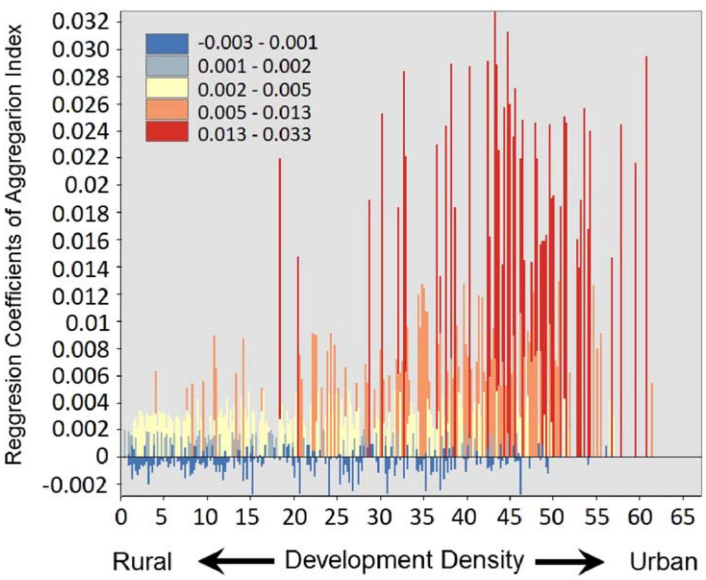

Figure 9. Distribution of geographically weighted regression coefficients of Aggregation Index coefficients for domestic water use along development density gradient.

4.3. Spatial Dependencies: Implications for Water and Land Use Planning

In relation to our third research hypothesis, we found spatially varying trends in development-related water use across the study system indicating that the benefit of implementing design-oriented guidelines could vary from one location to another. As such, geographically-targeted water conservation strategies (as opposed to aspatial strategies) are likely to be most useful when planning for more water-efficient development. The coefficients estimated in this analysis can help local and regional entities (e.g., cities, municipalities, counties and state governments) better understand the implications of their planning and development choices on future water demand, while also helping to understand the sensitivity of future regional water demand to likely patterns of urbanization. For example, if the sustainability of future water supply is of concern, then rapidly growing rural or suburban communities where water use is negatively associated with the Aggregation Index coefficient (Figure 9) may provide suitable locations to implement smart growth strategies that incentivize infill or higher density development patterns. Promoting this pattern of growth characterized by simple and aggregated forms of development can help such cities to accommodate future growth in a manner that maximizes the efficient use of water. Similar findings have been previously established for large metropolitan areas, where higher density household attributes have been associated with lower water use rates (Guhathakurta & Gober, 2010; Shandas & Parandvash, 2010). It is not the intention of our research to propose the use of landscape metrics as an alternative to traditionally used metrics such as household density or building area, but rather to allow for a new dimension of analysis at larger scales.

We observed that coastlines exhibited higher Shape Index coefficients (Figures 7 and 8). For example, DWU within 50 km of the coastline is on average 32% higher than other regions, and for TWU, the value is almost twice as large. Clearly, the Shape Index coefficients are larger along the Carolina coast (Figures 7 and 8), if we consider a scenario where the trajectory of growth leads to a one unit increase of the Shape Index, a coastal census tract would demand an average of 8,000 more gallons a day for DWU than a mainland census tract and an average of 37,000 more gallons a day for TWU. This effect might be associated with the flat topography that presents less geographical constrains to development, allowing 'leapfrog' development to expand more easily compared to more hilly and mountainous regions. This pattern of fragmented and sprawling development has characterized much of the urban growth in the Southeast (Terando et al., 2014).

In addition to changes in the magnitude of estimated coefficients across the study system, another important aspect of the predictive potential of the GWR method is changes on the direction of the effect. Coefficients that change from positive to negative across the study system suggest variables that may be spatially non-stationary. For example, in the global Holistic model the negative coefficient of median age indicates that as a population grows older it demands less water for domestic use (Table 3). This relationship is expected and is consistent with the literature (Arbues et al., 2010). However, the mapped GWR coefficient values revealed specific census tracts, mainly found in and around the Charlotte metropolitan area, where median age and domestic water use are positively related (Figure 7). An analysis of these areas revealed their census tracts rank among the top 15% average highest household income neighborhoods across the region. High income neighborhoods often have larger lots and home sizes, numerous bathrooms and the presence of a swimming pool, all structural attributes associated with higher outdoor water use (Harlan et al., 2009; Kontokosta & Jain, 2015; Ouyang et al., 2014).

5. Conclusions

Our results highlight the importance of considering spatial connections between water use in developed areas and its structural, socio-economic and environmental drivers. We found that metrics that described the spatial patterns of development played a key role in explaining water use models' explanatory power and can assist in the development of locally meaningful conservation strategies. Overall, we found that development guidelines that promote simple, cohesive, square-like configurations show potential for a more efficient use of water across the study system, and likely across other regions with similar patterns of land use.

Future estimates of development-related water use will benefit from the use of spatially explicit landscape metrics. Our study opens a frontier for water resources researchers to develop coupled models of water use and land change in an effort to explore alternative futures of urbanization and regional demands for increasing scarce supplies of water.

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