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Research article

Spatially-explicit modeling of multi-scale drivers of aboveground forest biomass and water yield in watersheds of the Southeastern United States

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ABSTRACT

Understanding ecosystem processes and the influence of regional scale drivers can provide useful information for managing forest ecosystems. Examining more local scale drivers of forest biomass and water yield can also provide insights for identifying and better understanding the effects of climate change and management on forests. We used diverse multi-scale datasets, functional models and Geographically Weighted Regression (GWR) to model ecosystem processes at the watershed scale and to interpret the influence of ecological drivers across the Southeastern United States (SE US). Aboveground forest biomass (AGB) was determined from available geospatial datasets and water yield was estimated using the Water Supply and Stress Index (WaSSI) model at the watershed level. Our geostatistical model examined the spatial variation in these relationships between ecosystem processes, climate, biophysical, and forest management variables at the watershed level across the SE US. Ecological and management drivers at the watershed level were analyzed locally to identify whether drivers contribute positively or negatively to aboveground forest biomass and water yield ecosystem processes and thus identifying potential synergies and tradeoffs across the SE US region. Although AGB and water yield drivers varied geographically across the study area, they were generally significantly influenced by climate (rainfall and temperature), land-cover factor1 (Water and barren), land-cover factor2 (wetland and forest), organic matter content high, rock depth, available water content, stand age, elevation, and LAI drivers. These drivers were positively or negatively associated with biomass or water yield which significantly contributes to ecosystem interactions or tradeoff/synergies. Our study introduced a spatially-explicit modelling framework to analyze the effect of ecosystem drivers on forest ecosystem structure, function and provision of services. This integrated model approach facilitates multi-scale analyses of drivers and interactions at the local to regional scale.

1. Introduction

The Southern United States forests are biologically diverse temperate and subtropical forests producing a set of ecosystem services or benefits to the people (Raudsepp-Hearne et al., 2010) at the local (e.g. food and timber), regional (e.g. clean water), and global (e.g. climate regulation) scales. These forest ecosystems are dynamic and may change over space and time in response to anthropogenic and other ecological drivers (Millennium Ecosystem Assessment, 2005; Raffa et al., 2008; Hautier et al., 2015). These drivers not only change land cover and land uses but also ecosystem composition, structure and function, which can then change the provision of ecosystem services (Millennium Ecosystem

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Assessment, 2005; Isbell et al., 2015). An important challenge of understanding ecosystem services is identifying these drivers and the interaction among different ecosystem functions across multiple scales (Millennium Ecosystem Assessment, 2005; Liu et al., 2016).

Forest biomass is a key ecological metric and indicator of ecosystem structure and functions (Houghton, 2005). Biomass is accumulated in the aboveground parts of the live tree and in coarse roots belowground (Susaeta et al., 2009). Carbon stored in terrestrial forest ecosystems may be released into the atmosphere, sequestered in long turnover time biomass or conserved in the soil (Brown et al., 1996), which makes it a major element in global climate and energy budget models. Alteration in forest biomass is directly related to changing net carbon exchange rates. These changes are important to managers and decision makers to achieve global emission targets (Brown et al., 1996).

In addition to the role of forests in regulating global climate via their function as a carbon source/sink, they play an important role in regional water cycles. Water yield is one of the most valuable services to society (Chapin et al., 2011; Brauman et al., 2007) and an integral ecosystem component that controls the living biomass, carbon cycle, and energy budget (Chahine, 1992). Water yield is a measure of the total outflow from a defined drainage basin over a time interval that can be used to assess the ecosystem function following disturbance (Brantley et al., 2015; Hallema et al., 2016). This interaction between carbon and hydrologic cycles highlights the need for modelling the outcomes from multiple forest uses and how different multi-scale drivers can result in synergies (win-win outcomes) and tradeoffs (win-lose outcomes) at the regional and local scales.

Ecological studies have documented how wildfire, wind storms, insects, and land use change are important drivers of changes in forest ecosystem carbon and biomass (Cropper and Ewel, 1987; Houghton, 2001; Wardle et al., 2003). Properly managed forest and soil quality practices also directly influence sedimentation and subsequent water quality (Brown et al., 2008). Forest soils, relative to other land uses, promote higher soil-water infiltration capacity (Bruijnzeel, 2004) and often contain high soil organic matter and hydraulic conductivity that greatly influence water regulation (Zhou et al., 2010).

Forest structural attributes such as biomass can be directly linked to carbon dynamics of forests (Houghton, 2001; Kashian et al., 2006), as well as others such as Leaf Area Index (LAI) can also affect evapotranspiration dynamics in forests and the water cycle. Forests can regulate water while providing other ecosystem service co-benefits, such as carbon sequestration, and moderating climate change (Swart et al., 2003; Ice and Stednick, 2004). As such, forest management regimes will directly affect biomass and water yield (Timilsina et al., 2013). These drivers of ecosystem functions can change through time and space, due to direct drivers changing ecosystem structure or indirect drivers such as socioeconomics and policies (Bennett et al., 2009; Liu et al., 2016). Basic understanding of forest-water relationships at the watershed-scale using basin and regional level experimental data is however complex (Sun and Liu, 2013).

Thus, there is a need to increase our understanding of how different drivers influence ecosystem functions and whether these results in trade-offs or synergies (Bennett et al., 2009). Key disturbances of SE forests include, in addition to climate change, the reversion of agricultural land, urbanization, wildfire, and pest and pathogens (Trani, 2002). These anthropogenic and natural disturbances interact with each other and influence the development of complex heterogeneous landscapes (Turner and Ruscher, 1988) that affect forest ecosystem functions. Topography has a strong influence on wetland land use and also regulates the streamflow patterns and stromflow peaks and volumes. Land managed by diverse landowners, both public and private, and economic goals of owners significantly influence the water yield ecosystem service (Douglass, 1983). Increased forest thinning (vegetation management) increases the total Water yield volume (Huff et al., 2000). Few of these studies however, have utilized a spatially explicit modelling approach to determine the ecological drivers. The use of global regression models might not explain the local drivers of services using commonly used biophysical variables as they assume stationarity across the study area. Fotheringham et al. (1998) indicated that spatial heterogeneity will also cause problems in the interpretation of parameter estimation using such global regression models. Hence, to better understand ecosystem drivers and interactions, the spatial variation of these must be accounted for as part of the modelling framework.

Geographically weighted Regression (GWR) is one approach that has been used to account for spatial non-stationarity among the relationships between modelling variables as it uses global and piecewise spatial sub-models (Crespo and Grêt-Regamey, 2013). Several studies have investigated the local geography of the relationship between socioeconomic indicators and their characteristics (Fotheringham et al., 2001; Dziauddin et al., 2015). However, few studies examined the spatially varying relationships between ecosystem services (or processes) and the drivers to account for the relationships' spatial heterogeneity. The application of the GWR method could be an effective approach for examining these relationships and to extract meaningful information about geographically influenced ecosystem services and their drivers at both regional and more local scales. These more local and plot scale drivers are often referred to as predictors, but we refer to all the multi-scale factors affecting ecosystem processes and subsequent services collectively as drivers.

Therefore, the aim of this study is to develop a modelling approach to analyze the spatial variation in drivers of two key regional forest ecosystem processes that are regularly used as indicators of ecosystem service provision; aboveground forest biomass and water yield. Specifically our objectives are to use the GWR method to: (1) demonstrate the spatial variability of the significant drivers that influence aboveground biomass and water yield at the watershed level across the SE US, (2) identify common significant drivers that influence aboveground biomass and water yield at the watershed level across the SE US forests (Bennett et al., 2009), and (3) identify watershed clusters located across the SE US forests that experience strong synergies and trade-offs among aboveground biomass and water yield. We believe that such an approach is novel in that it provides a spatially-explicit technique to find consistent patterns of synergies and tradeoffs among aboveground forest biomass and water yield using available forest inventory and geospatial data. Such a spatially explicit framework could significantly contribute a methodology for identifying and understanding the positive (win-win) and negative (win-lose) outcomes of management and biophysical drivers on ecosystem functions and services across multiple scales. Our method also facilitates further studies of local functions, processes, and interactions leading to the observed synergies and trade-offs.

2. Methodology

2.1. Study area

The SE US study region includes the states of Florida, Georgia, North Carolina, South Carolina, Mississippi, Alabama, Tennessee, and Mississippi. These states are characterized by a mild wet and humid climate with a mean annual temperature of 17° C and annual precipitation higher than 1300 mm, which provides high forest productivity (Sun et al., 2004). The region is characterized by historical and important agricultural and forest timber economic sectors despite its rapid rate of urbanization (Alig and Healy, 1987). The U.S. Census reported that over 49 million people were living in these states in 2000 and it is expected that by 2020, the region's population will double (Wear and Greis, 2001). This region spans the low-elevation and sandy soils of the Coastal Plain, the steep sloping terrains in the Southern Appalachian Mountains, and the fine, clayey soils of the Piedmont (Evans and Bartholomew, 2013).

Land cover change that occurred over the past two centuries in the SE US was due to the clearing of forests for conversion into agriculture, pine plantation, urban development, and forest fires among others (Drummond and Loveland, 2010). Indeed most of the US's wood and fiber is produced in the study area and there are growing concerns that climate change will alter this production (Wertin et al., 2010). The SE US forests are a combination of private and public land tenures, interspersed with rapidly growing urban area as well as consistent agriculture related land uses, and are known for the historical and frequent impacts of hurricanes (Delphin et al., 2013; McNulty et al., 1998).

Hierarchical ecoregions are a multi-scale framework that organizes spatial areas according to similar geographical and ecological parameters (e.g. climate, geology, landforms, soils, vegetation, and land use). Thus, Ecoregions provide a useful framework for spatially analyzing different and particular environmental conditions and potential responses (Omernik and Bailey, 1997). The US Forest Services level 3 ecoregions (Omernik and Bailey, 1997) were used in this study as a means to represent regions with relative similarity in the biotic and abiotic properties of the ecosystems (Omernik and Bailey, 1997; Bailey et al., 1985). Fig. 1 shows a map of the SE US level3 ecoregions used in this study and the administration boundaries of the SE US states.

2.2. Biomass, water yield, and ecosystem service driver dataset

The aboveground biomass was estimated by summarizing the Contiguous (i.e., conus) biomass 250 m pixel-size raster dataset developed by Blackard et al. (2008) at the watershed level. This data set was created using the US Forest Services Forest Inventory and Analysis national dataset and other geospatial datasets such as Digital Elevation Model (DEM), Moderate Resolution Spectrometer (MODIS) multi-date image composites, vegetation indices data, National Land Cover Dataset (NLCD) 1992, ecoregion map and the PRISM climate (monthly and annual temperature and precipitation) datasets (Blackard et al., 2008). The data set provides the distribution of aboveground biomass across landscape which is suitable for identifying forest resources affected by Urbanization, fire, fragmentation etc. Blackard et al. (2008). Fig. 2a shows the estimated biomass at the HUC8 watershed level in the SE US.

We estimated water yield at the watershed level using the

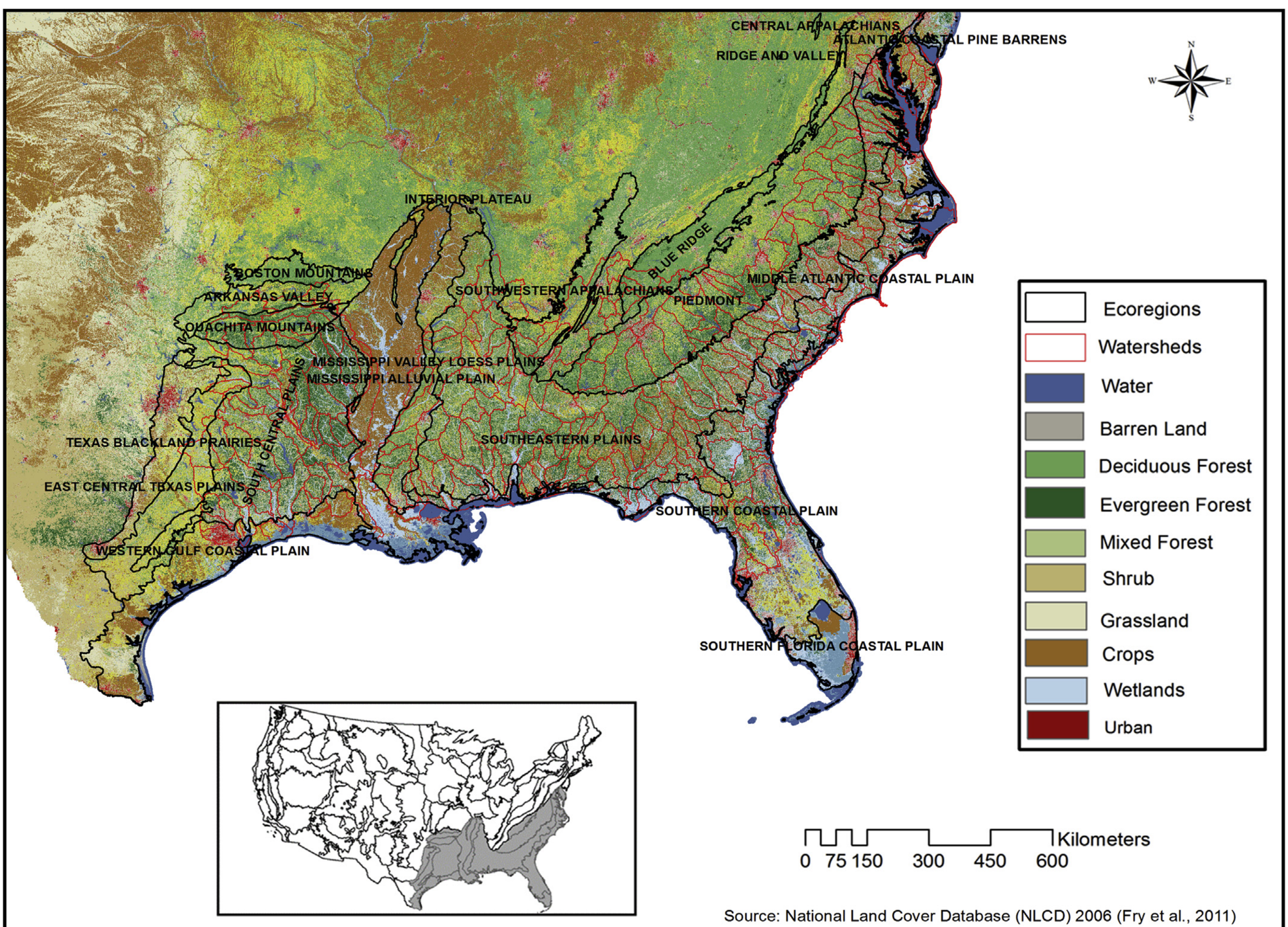

Fig. 1. Level3 ecoregions of the southeastern USA.

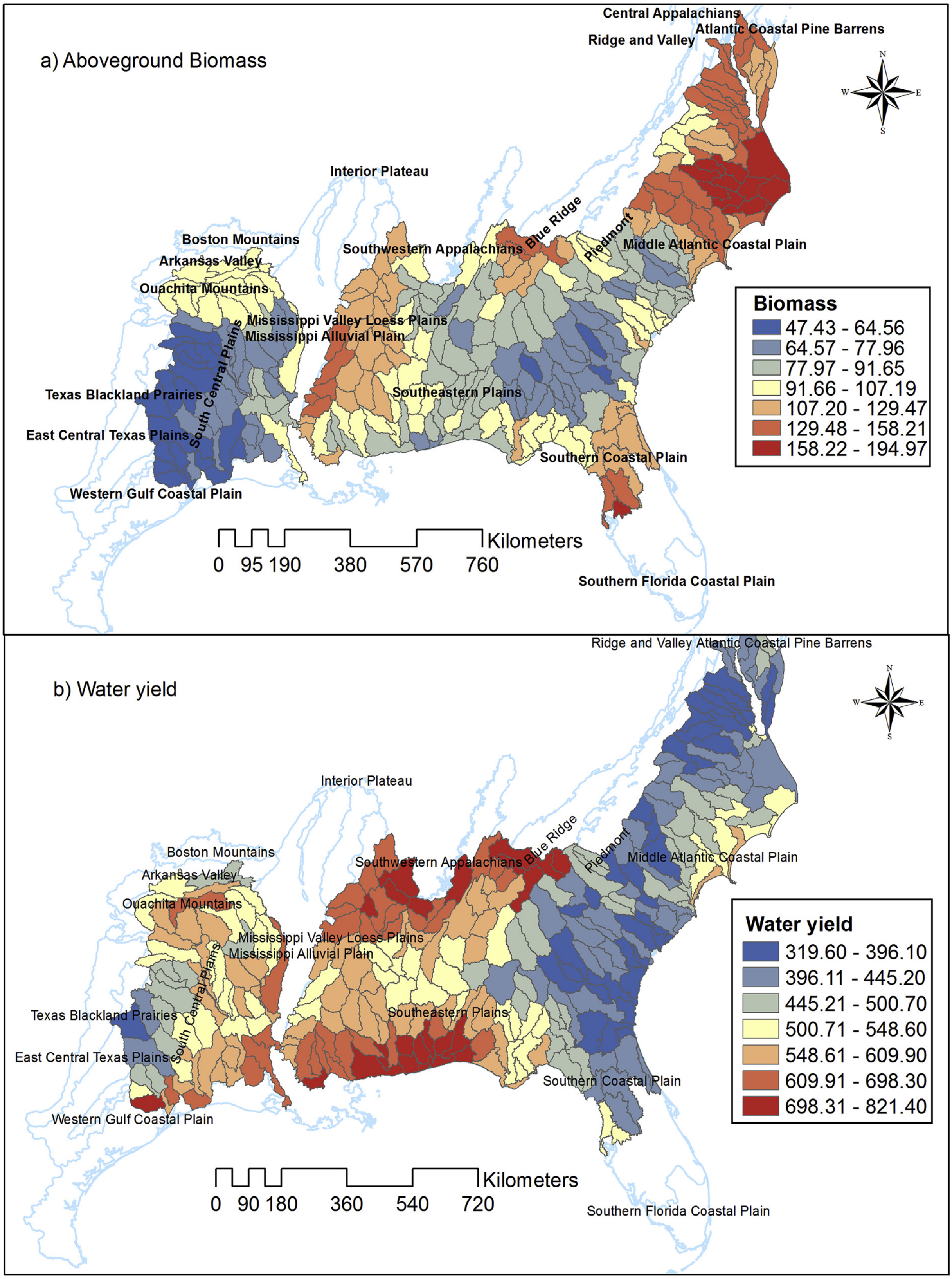

Fig. 2. a) Aboveground forest biomass for Hydrological Unit Code (HUC) 8 watersheds in Mg/ha across the Southeastern US, and b) Water yield of HUC8 watersheds in mm across the Southeastern United States.

Water Supply Stress Index (WaSSI) simulation model (Sun et al., 2011). Water balance components used in the WaSSI model include evapotranspiration, snow melt and accumulation, infiltration, surface water yield, base-flow, and soil moisture processes within each land cover class for each watershed. Input used in the model includes the PRISM climate grid (Daly et al., 1994), national land cover dataset (Fry et al., 2011), MODIS leaf area index (Zhao et al., 2005), geographically reference databases, STATSGO conus soil characteristics databases (Miller and White, 1998), and county maps of water use, withdrawal, and projected population. Water yield estimates were modeled using a historic (1961–2010) climate scenario model for a period of 13 years from 1990 to 2003 which is in accordance to the time interval of the conus biomass map (Blackard et al., 2008). This analysis does not deal with time series assessment and therefore a mean water yield estimate for all periods was used in the analysis to maintain consistency with mean aboveground biomass estimates over the time span (1990–2003). The water yield estimates were obtained from the output of the water balance model as average annual estimate in millimeters (mm) for each HUC8 watershed. The water yield estimates of WaSSI is used for studying the effect of climate, land cover, and water usage change (Caldwell et al., 2012) and therefore, this data is considered appropriate in our study to model the drivers locally. Fig. 2b shows the estimated water yield at the HUC8 watershed level in the SE US.

In this manuscript, several ecosystem driver datasets were prepared and analyzed. These datasets were acquired from various sources (Table 1) such as the PRISM climate dataset (Daly et al., 1994), national land cover dataset (Fry et al., 2011), Moderate Resolution Imaging Spectrometer (MODIS) leaf area index product (Zhao et al., 2005), State Soil Geographic Database (STATSGO), conus soil databases (Miller and White, 1998), and the Shuttle Radar Topography Mission (SRTM)-90 m elevation grid. The United States Department of Agriculture's (USDA) Forest Service Forest Inventory Analysis (FIA) national-level inventory data (Forest Inventory Analysis program, 1928) were used to derive the local-scale forest management information (e.g. stand age, site quality, treatment, ownership, and disturbance) at the watershed scale.

The 30 m spatial resolution land cover GIS layer obtained from the 2006 national land cover dataset was used to estimate the land cover drivers used in the study. This GIS layer has three different forest types including evergreen, deciduous and mixed forest classes. These three classes were grouped into a single forest land cover class, leaving a total of eight land-cover types: forests, crops, grass, shrubs, wetlands, water, urban and barren. The percentage of each land cover type in each watershed was used in the analysis.

The annual LAI for the study period was obtained at a resolution of 1 × 1 km and was estimated at the watershed level as a function of land cover percentage, which was obtained by averaging the seasonal LAI for each land cover class. In this estimation, the product of each land cover percentage and its respective LAI was summed to attain the LAI per watershed. The average annual rainfall and temperature data at a 4 × 4 km spatial resolution were obtained from the PRISM climate dataset and averaged for each watershed. Elevations were obtained as raster data tiles at a 30 m spatial resolution. The tiles were then merged together to make a single large-scale topographic raster dataset of the SE US. Slope was computed from the elevation layers and both layers were summarized by averaging the values within each watershed in the SE US.

The STATSGO soil characteristics dataset includes 1 × 1 km resolution grid map and its soil attributes including: map identifiers, soil component, data layers, and metadata information. This study used the following specific soil attributes: (1) Available Water Capacity High (AWCH), maximum range value of water content that is available for a soil layer; (2) Organic Matter Content High (OMCH), maximum range value of organic matter present in soil; and (3) Soil Thickness or Rock Depth High (ROCKDEPH), maximum range value in soil depth measured from top surface to base rock. Soil characteristics data were attributed to the 1 × 1 km grid map as a preprocessing step before summarizing at the watershed level using the ArcGIS software (Version 10.2, ESRI, Redlands, USA).

Forest management variables from the plot-scale FIA data used in this study include: stand age, site quality, plot ownership, disturbance, and silvicultural treatment that were obtained from the FIA database for the 1990 to 2003 analysis period. Since this study was conducted at the HUC8 watershed level, we presumed that plot fuzzing (i.e. relocation of the plot 1 mile away from its actual location) and swapping (i.e. exchanging plot coordinates) procedure prescribed by FIA to preserve privacy issues (Forest Inventory Analysis program, 1928) will have negligible impact on our results.

The FIA plot data was obtained in a tabular format and outlined to the HUC8 watershed scale (Table 1). The Stand age (STDAGE; years) attribute field of the FIA data was summarized to each watershed by averaging the stand age of all FIA plots that are located within the watershed. The FIA ownership group code (OWNGRPCD) was used to differentiate public and private tenure of each FIA plots which was then summarized as the percentage of public and private FIA plots within each watershed. The FIA disturbance code describes the specific ecological or management disturbance (i.e. fire, wind, logging, etc.) experienced by each plot which was summarized as a percentage of plots that were either disturbed or undisturbed at the watershed level. The treatment code defines a particular treatment type (e.g. thinning, fertilization, silvo-pastoral activities) measured on each FIA plot, and this code was analyzed as the percentage of FIA plots inside watershed that were either treated or not-treated.

2.3. Geographically weighted regression (GWR) model

Geographically Weighted Regression models are used to address spatial heterogeneity issues at a local scale and provides additional functionalities to the regression method by considering the overall spatial structure and examination of local parameters (Fotheringham et al., 1996). Accordingly, parameter estimate at any location u^2 should have greater weight for the observations that are closer to that location than far away observations. The regular GWR form of an Ordinary Least Squares (OLS) regression is expressed as:

$$y_i(\mathbf{u}) = \beta_{0i}(\mathbf{u}) + \beta_{1i}(\mathbf{u})x_{1i} + \beta_{2i}(\mathbf{u})x_{2i} + \ldots + \beta_{mi}(\mathbf{u})\,x_{mi} \tag{1}$$

where, $y_i(\mathbf{u})$ is the dependent variable value of observation i considered in parameter estimation at location u. Similarly, $x_{1,\,i}$, $x_{2,\,i}$, $x_{\mathrm{m},\,i}$ are the independent variables of observation *i*. $\beta_{\mathrm{m}i}(\mathbf{u})$ indicates a parameter estimate that explains the relationship around location **u** and it is particular to that location.

The parameter estimator for a GWR model is identical to the Weighted Least Squares Regression, where the weights are computed based on the distance between the observations. The parameters (regression coefficients) are estimated as:

$$\widehat{\beta}(\mathbf{u}) = \left(X^T W(\mathbf{u}) X\right)^{-1} X^T W(\mathbf{u}) \mathrm{y} \tag{2}$$

where, W($\mathbf{u}$) is the square matrix of weights corresponding to the position over the study area and $(X^T W(\mathbf{u})X)$ is the geographically weighted variance-covariance matrix; the weights are calculated based on a kernel weighting scheme such as Fixed Gaussian, Fixed bi-square, Adaptive bi-square and Adaptive Gaussian (Peter Mills,

Table 1
Data sources of ecosystem drivers across the Southeastern US.

Ecosystem drivers	Ecosystem Driver (units)	Data source	Description
Average annual rainfall	Millimeter (mm)	PRISM climate (Daly et al., 1994)	Average annual precipitation for the period 1990–2003
Average annual temperature	Millimeter (mm)	PRISM climate (Daly et al., 1994)	Average annual precipitation for the period 1990–2003
Land Cover	Percentage	National Land Cover Database 2006 (Fry et al., 2011)	NLCD 2006 of 30 m resolution.
Elevation	Meter (m)	SRTM-90 m elevation grid	SRTM digital elevation data.
Slope	% slope	SRTM-90 m elevation grid	SRTM digital elevation data.
Leaf Area Index (LAI)	–	MODIS leaf area index product (Zhao et al., 2005)	Ratio of leaf area to ground cover for broadleaf plant canopies.
Available Water Content High (AWCH)	Inches/Fraction	STATSGO soil characteristics 1-km grid map (Miller and White, 1998)	Maximum range value of water content available for a soil layer.
Organic Matter Content High (OMCH)	Percent by weight	STATSGO soil characteristics 1-km grid map (Miller and White, 1998)	Maximum range value of organic matter present in soil.
Rock Depth High (ROCKDEPH)	Inches	STATSGO soil characteristics 1-km grid map (Miller and White, 1998)	Maximum range value in soil depth measured from top surface to base rock.
Stand age	Years	FIA national-level inventory data (FIA program, 1928)	Estimated age of the plot using field records or local procedures.
Site quality	Cubic feet acre/year	FIA national-level inventory data (FIA program, 1928)	Potential growth related to capacity of forest land to grow biomass.
Ownership	Percentage of the FIA plots with private ownership.	FIA national-level inventory data (FIA program, 1928)	Ownership status of plot during the inventory.
Disturbance	Percentage of the FIA plots that are disturbed.	FIA national-level inventory data (FIA program, 1928)	Disturbance happened since the last inventory of a plot.
FIA Treatment	Percentage of the FIA plots that are treated.	FIA national-level inventory data (FIA program, 1928)	Stand treatment applied since the last inventory of a plot.

2011). In this study we used Fixed Gaussian kernel which has a Gaussian shape:

$$w_i(\mathbf{u}) = e^{-0.5\left(d_i(\mathbf{u})/h\right)^2} \quad (3)$$

$w_i(\mathbf{u})$ represents the geographical weight of ith observation with respect to the location u, $d_i(\mathbf{u})$ is the distance between the ith observation and the location $\mathbf{u}$, and h is a quantity called bandwidth, which controls the effect of the distance on the weight value.

The parameters are estimated at locations where observations are measured and thus, predictions are made for dependent variable and residuals are estimated in the dataset (Fotheringham et al., 2003). Based on these results, the GWR model calculates the goodness-of-fit of a model. The locations where the parameters are estimated are known as the regression points and the geographically weighted estimator along with kernel and bandwidth is referred to as the local model.

We used the GWR 4.0 software to perform our analysis (Nakaya et al., 2009). The software supports calibration of geographically weighted regression (GWR) models and analyzing the geographically varying relationship between dependent and independent variables. The semi-parametric geographically weighted regression (S-GWR) is also a form of GWR model for analyzing the geographically varying relationship between the dependent and independent variables. This semi-parametric model is expressed as follows

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i) x_{ik} \; i = 1, \ldots, n \quad (4)$$

where y_i is the dependent variable at location i and u_i, v_i are geographical coordinates at point i, and $\beta_0(u_i, v_i)$ is the intercept parameter for a particular location. Finally, $\beta_k(u_i, v_i)$ is the parameter for kth location, P is the total number of unknown local parameters to be estimated, x_{ik} is the kth independent variable for the term β_k Based on the semi-parametric technique and a geographically weighted calibration, we can map a smooth and continuous surface of local parameter estimates across the geographical space.

2.4. Driver data preprocessing

An Ordinary Least Squares (OLS) regression model was used to identify highly-correlated drivers and to determine the best-fit

Table 2
Loadings from factor analysis of land-cover variables.

Loadings:	Factor1	Factor2	Factor3
Forest	−0.472	−0.783	0.398
Crop			−0.994
Grass	−0.372		0.153
Shrub	−0.343	0.241	0.225
Wetland		0.866	
Water	0.987		0.104
Urban		0.327	
Barren	0.681	0.168	0.219

Table 3
Variation Inflation Factor (VIF) analysis for multicollinearity detection among the driver variables.

Drivers	VIF Score
Rain	2.24394
Temperature	3.808375
Land.Cover.Factor1 (water and barren)	4.528428
Land.Cover.Factor2 (wetland and urban)	3.679821
Land.Cover.Factor3 (forest and shrub)	3.628775
Rock depth High (Rockdeph)	2.166647
Organic Matter Content High (OMCH)	2.193686
Available Water Content High (AWCH)	2.01884
Stand age	1.664796
Sitequality	1.520937
FIA Plots Disturbance	1.293366
FIA Plots Ownership	1.74569
FIA Plots Treatment	1.836659
Elevation	8.161271
Leaf Area Index (LAI)	5.280339

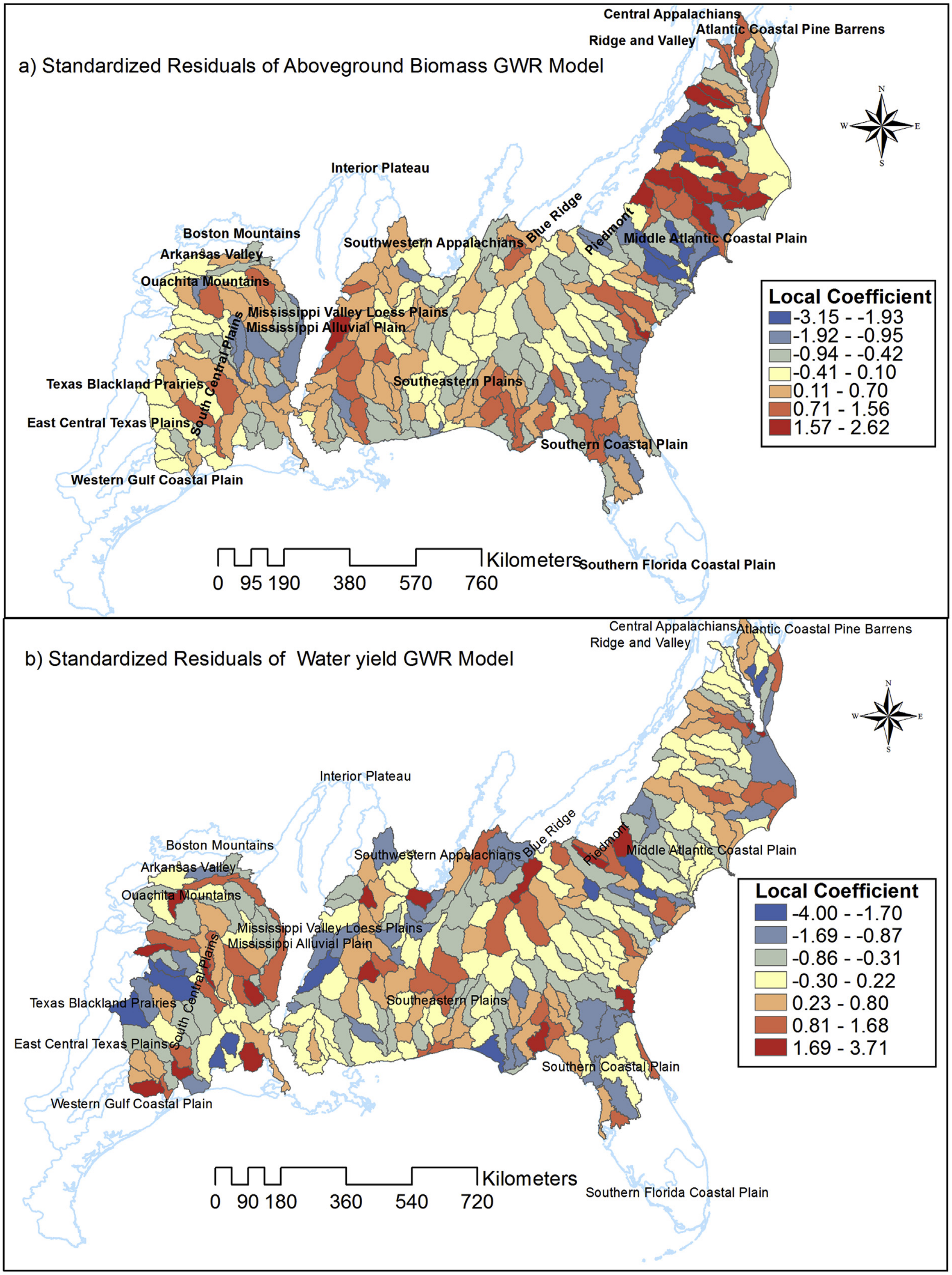

Fig. 3. Standardized Residuals of geographically weighted regression model with climate, biophysical and forest management as drivers to predict: a) the aboveground biomass and, b) the water yield in watersheds of the Southeastern US.

global OLS model in the SE US region. The OLS model along with significant variables was compared using the F-tests and adjusted R-squared values. The covariates of the OLS model were analyzed using a Variance Inflation Factors (VIF) (Kutner et al., 2004). A 95% confidence level ($p < 0.05$) was used to identify the significant covariates. Variance Inflation Factor (VIF) analysis was performed using the "fmsb" package in the R statistical software (Version 3.2.3, R core Team).

All land cover variables were found to have high collinearity (VIF>10). So, factor analysis (Rummel, 1967) was applied to the land cover variables to obtain the lower set of variables that describe maximum variability, using the "psych" package in R, version 1.6.9. By default, these factors are rotated orthogonally to generate new factors or scores that will be uncorrelated and can replace the originally correlated land-cover variables. Three factors explaining the maximum variance out of the total variance among the land-cover types were identified. Based on each factor loading, we identified the land cover variables contributing to the factor. Table 2 shows the variable loadings computed as the correlation between each of the 8 land cover variable and the first three factors resulting from the factor analysis. The high positive and negative loadings indicate high variable significance in computing the factor (Kim and Mueller, 1978). Water and barren land-cover types had large positive loadings in factor1. Forest and wetland had large loading values for factor2 while the cropland land cover was found to be highly (negatively) correlated with factor3.

The VIF analysis identified elevation and slope as topographic variables that were highly correlated at the 95% confidence level. The Pearson's product-moment correlation coefficient between these two variables was found to be 0.92; hence, the slope variable was dropped from the GWR analysis. The OLS was run to assure the modified set of variables were not highly correlated with the VIF test at the 95% confidence level and to determine the best fit OLS model. Table 3 lists all VIF values using the modified set of variables. We used a Gaussian linear model with a fixed Gaussian geographic kernel. Further, the gold selection search function (Nakaya et al., 2009) was used to select optimal bandwidth with the Akaike Information (AIC) as a criterion (Nakaya et al., 2009). Global Moran's I (Moran, 1950) statistic was used to test the spatial autocorrelation of the residuals of the GWR model results.

2.5. GWR model and interaction analysis

Choropleth maps of the standard residuals resulting from the biomass and water yield GWR models were produced and presented in the Results section. These residuals were used to analyze the spatial heterogeneity (i.e. non-stationarity) among the watersheds. The red and blue colors were used to indicate if the model is over or under predicting the biomass and water yield. The Local R-squared values of the GWR model computed at each watershed were used to assess the model's localized goodness of fit. The R-squared values were mapped to assess areas with highly significant variation or no variation and areas that need further examination.

To interpret the GWR model, the regression coefficients of each variable was mapped to illustrate the spatial variation of the regression parameters. Only the statistically significant ($p < 0.05$) local regression coefficients of each driver resulting from the GWR model were mapped (see the Results Section). Positive values of the coefficients indicate a direct relationship between the independent variables (i.e., drivers) and the modeled biomass or water yield values, while the negative values indicate an inverse relationship. All choropleth maps were created using ArcGIS 10.2.

The interactions between biomass and water yield was defined based on the positive/negative correlations between the significant drivers identified by the GWR model at the watershed level and the two ecosystem processes. Specifically, synergies between biomass and watershed considering a specific driver is identified if the driver has a positive correlation with both the biomass and water yield. In contrast, areas of trade-offs were considered with positive correlations between the driver and water yield and negative correlations between the driver and biomass and vice versa.

3. Results

Aboveground biomass and water yield were estimated and mapped in 284 watersheds across the SE US. Noticeable patterns of spatial clustering of ecosystem processes can be visually recognized along each ecoregion (Fig 2a and b). The OLS regression model identified climate, land-cover factor3, Organic Matter Content High (OMCH), Available Water Content High (AWCH), stand age, Elevation, and LAI as statistically significant ($p < 0.05$) drivers of biomass. For water yield, the OLS model identified climate, land-cover factors, three soil characteristics (ROCKDEPH, OMCH, AWCH), Elevation and LAI as statistically significant ($p < 0.01$). The overall R-square for the biomass OLS model was 0.42, while for the water yield, the R-square value was 0.96. In particular and as expected, the precipitation variable was strongly correlated ($R = 0.89$) with water yield. The Global Moran's I for the biomass OLS model residuals was 0.65 (z-score = 15.83, $p < 0.01$) and for the water yield residuals, Moran's I value was 0.37 (z-score = 9.34, $p < 0.01$). These p-values and the positive z-scores of the Global Moran's I statistics indicate that the null hypothesis that observed clustering of the residuals is due to random processes is rejected and illustrate the existence of significant spatial autocorrelation. Therefore, there was less than 1% likelihood that the spatial clustering of high or/and low values recognized in the biomass and water yield residuals were the result of random chance.

Choropleth maps of the standard residuals resulting from the biomass and water yield GWR models are shown in Fig. 3a and b, respectively. The red and blue areas in Fig. 3a and b indicate if the model is over or under predicting the biomass and water yield. The pattern of the blue and red colors across the watersheds in Fig. 3a and b indicates that there are no clustering of high and/or low values of biomass and water yield residuals (i.e. random) from the GWR model hence a low or no spatial autocorrelation can be expected in the residuals of both models. The GWR model could have accounted for most of the spatial autocorrelation effect in the dataset.

The local R-square values were mapped (Fig. 4a and b) to better identify areas where the covariates described most of the variability in biomass and water yield for each watershed. The statistically significant ($p < 0.05$) local regression coefficients of each driver resulting from the GWR model at each watershed were also mapped in Figs. 5 and 6. These Figures show, as expected, that the statistically significant ($p < 0.05$) independent variables (or drivers) identified by the GWR model varied across the SE US. The positive value (blue color) indicates a positive relationship between the mapped independent variable (drivers) and the modeled biomass or water yield values. On the other hand, the negative values (red color) imply an inverse relationship between the independent variables (or drivers), and the modeled values. Overall, the common significant drivers that influence AGB and water yield at the watershed level across the SE US were: climate (rainfall and temperature), land-cover factor1 (Water and barren), land-cover factor2 (wetland and forest), organic matter content high, rock depth, available water content, stand age, elevation, and LAI.

The watershed clusters (Figs. 5 and 6) that experienced strong synergies among aboveground biomass and water yield were mostly located in the Southern Coastal plain, Central and Western Southeast plain and the Western Piedmont Ecoregion, and were all

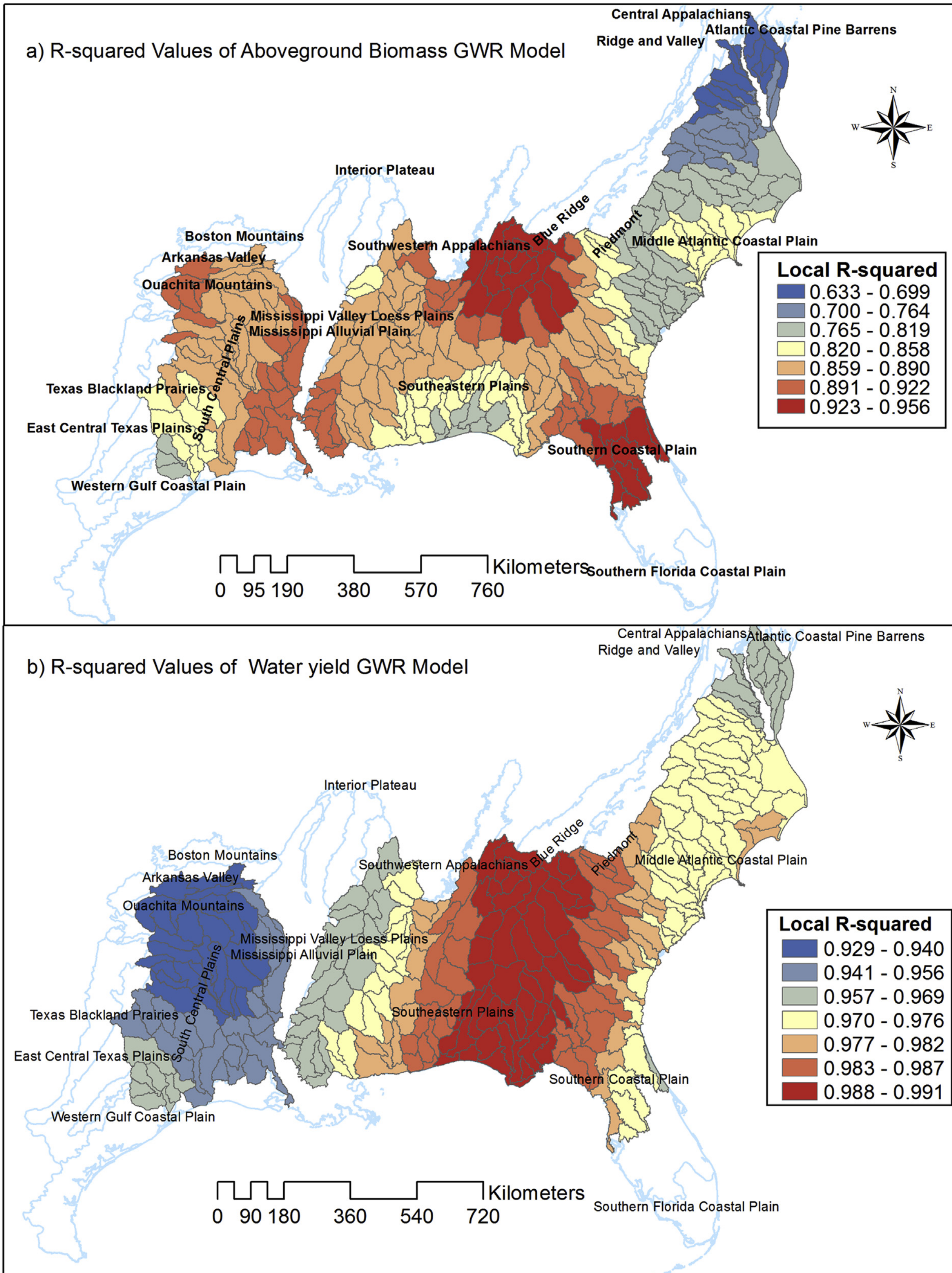

Fig. 4. Local R-Squared values of the: (a) aboveground biomass and (b) water yield Geographically Weighted Regression models for watersheds in the southeastern United States.

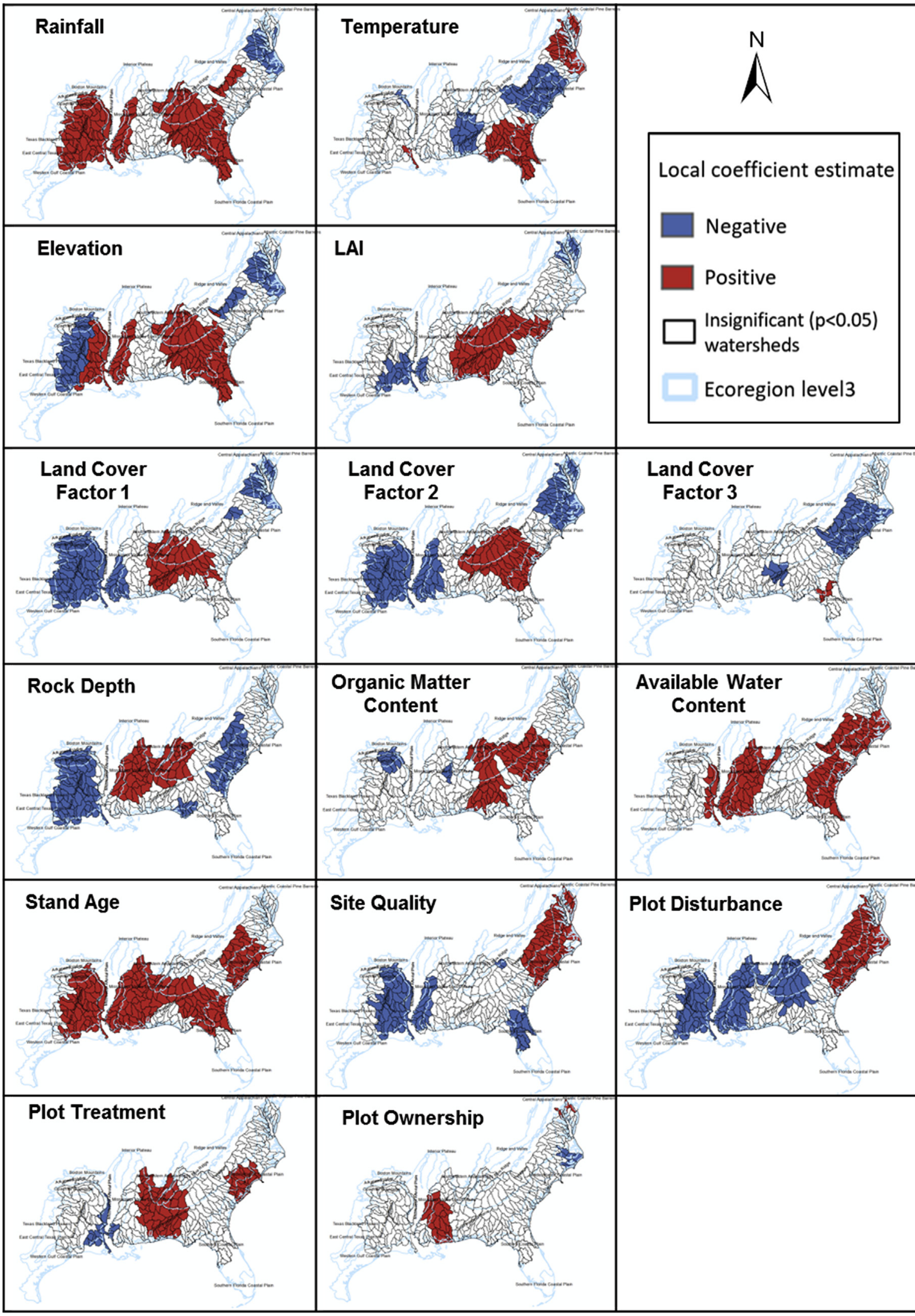

Fig. 5. Positive (red) and negative (blue) association of independent variables (drivers) with aboveground biomass obtained from the geographically weighted regression models for watersheds in the southeastern United States. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

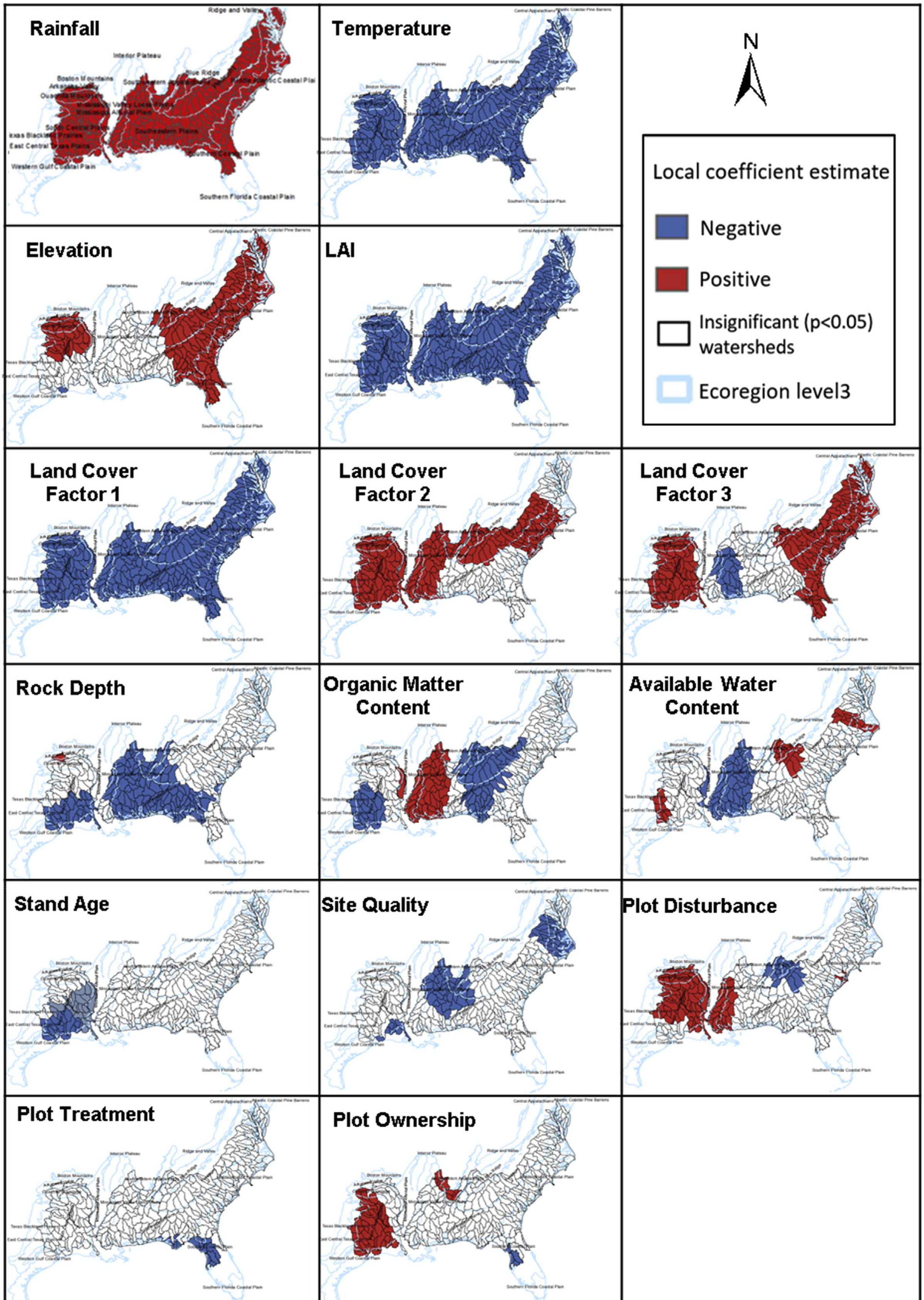

Fig. 6. Positive (red) and negative (blue) association of independent variables (drivers) with water yield obtained from the geographically weighted regression models for watersheds in the southeastern United States. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

influenced by rainfall and elevation. Additionally, potential trade-offs (win-lose interactions) among aboveground biomass and water yield were observed along the Southern Coastal plain and were influenced by temperature whereas the Central, Western, and Eastern Southeast plain were influenced by temperature, land-cover factor 1, and land-cover factor 3.

The entire Piedmont Ecoregion was influenced by land-cover factor 2 (wetland and forest) while the South of South Central plain was influenced by rock depth and the entire South Central plain by rainfall and land-cover factor1 (water and barren). The Mississippi Alluvial plain was influenced by available water content. The entire Southeast plain was influenced by LAI; Central, Eastern and entire Piedmont plain by temperature, land-cover factor 3, and LAI; South Central plain by land-cover factor 2, stand age, and plots-disturbance; Central and Eastern Middle Atlantic Coastal plain by temperature and land-cover factor 3; and Mississippi Alluvial plain by land-cover factor 2.

4. Discussion

This study's modelling approach found that the soil water content, LAI, stand age and precipitations, were significantly and positively correlated and hence drivers of aboveground forest biomass across most of the SE US′ ecoregions. Additionally, coefficients with mixed signs were also observed for soil organic content and land cover factor 3 (Crop) in our GWR model for water yield across the SE US. These findings could be used to better understand the effect of direct and indirect drivers on aboveground biomass and water yield as well as the interaction among these drivers (Hay and McCabe, 2002; Zedler, 2003). For example, regional and global-scale climate change effects that alter precipitation regimes or local-scale forest management practices that manage for crown characteristics (i.e., LAI) or stand age will affect biomass and subsequent forest carbon sequestration function (Sun et al., 2011). Similarly, forest conversion or vegetation clearing activities (e.g. land cover factor 3) will affect water yield and related purification services (Delphin et al., 2016).

Our approach shows how the use of GWR models facilitated analyzing the effects of each driver on biomass and hydrologic related ecosystem processes at different spatial scales (Jetz et al., 2005). For example, the clustered distribution of significant coefficients across SE US region (Figs 5 and 6) was spatially discernable. North America is broadly divided into 15 level 1 ecoregions according to the US Forest Services ecoregion classification (Omernik, 1995, 2004). To provide more detailed descriptions of the level 1 ecoregions, the hierarchical ecoregion classification system sub-divided the 15 level 1 ecoregions to 50 level 2 ecoregions. These in turn were subdivided into 85 level 3 ecological regions and another 967 level 4 ecoregions that are useful for environmental monitoring and assessments (Omernik, 1995, 2004). These watershed clusters have the same sign (positive or negative) of the coefficient values and spatial overlap for several drivers of the ecosystem processes (biomass or water yield) suggesting some multi-scale drivers that go beyond the level 2 and level 3 ecoregion scales as suggested by Bailey (1998) and Omernik (2004). These clusters often form a subset or extend along level 3 ecoregions. Interestingly, these clusters cover several level 4 ecoregions too. This observation suggests that conducting more thorough studies on ecoregion categorization and probably introducing other intermediate ecoregion levels could be needed for some management or planning objective.

The spatial patterns of the water yield drivers were easier to interpret across the SE US and are similar to those reported by Sun et al. (2011) and Cademus et al. (2014). Sun et al. (2011) and Delphin et al. (2016) found that climate change has prominent effects on water supply compared to other drivers. In our dataset, the rainfall, temperature, land cover factor1, and leaf area index were consistently positively or negatively related with water yield across the SE US as indicated by the water yield GWR model (Fig. 6). Nevertheless, the OLS model for the SE US region identified other drivers (e.g. organic matter content high, available water content high), and elevation. These drivers were found significant only in some watersheds across the SE US when using the GWR model. Similarly, none of the biomass model drivers were found significant in all the watersheds in the SE US. This observation indicates the importance of using localized models to model ecosystem drivers and highlights the influence of failing to account for the spatial autocorrelation in the OLS models.

The four significant drivers (e.g. rainfall, temperature, land cover factor1, and leaf area index) identified by the water yield GWR analysis of the SE US were strongly associated with the input used by the WaSSI model to compute water yield at the watershed level (Sun et al., 2011). Although this is a study limitation, there is little that can be done to avoid such deficiency since most existing water yield estimation models incorporate these same inputs parameters. In the meantime, our study reveals other water yield drivers at the local scale that could be of interest for future ecological studies and could contribute to future improvements in water yield estimation models.

The significance of the rainfall as a driver to biomass is not consistent in the SE US region; our findings are not supported by previous studies suggesting that changing precipitation can influence aboveground forest biomass (Hurteau et al., 2008; McNulty, 2002). We recognize that there are likely precipitation thresholds not found in our data that would be associated with significant changes in forest structure and function. Temperature was identified as significant in the OLS global model identifying a single set of drivers for all the watersheds in the SE US but not in the spatially varying local GWR model. This could be attributed to the local effects of the land cover change (Thompson et al., 2011). Both land-cover factor1 (water and barren) and land-cover factor2 (forest and wetland), were consistently positively correlated with biomass in the central part of SE US and negatively correlated in the western part of SE US.

The inconsistent significance of land cover on biomass throughout the SE US region can be attributed to changes in local land use and land cover across the region (Drummond and Loveland, 2010). The significance of soil depth and soil available water capacity driver with biomass along few ecoregions could be due to soil characteristics that would differ at the local and regional scales with the change in their soil processes (Post and Kwon, 2000). We do observe that LAI is directly proportional to biomass in the south central part of the Southeastern Plain ecoregions. This area also experiences positive correlation with the stand age (Houghton, 2001; Kashian et al., 2006). On the other hand, the remaining variables varied in terms of having a positive or negative correlation with the biomass across the study area.

The water yield experienced positive correlation with rainfall and negative correlation with temperature over the entire SE US, which is probably due to the well documented climate processes across the region. LAI was observed to be inversely proportional to water yield across all the SE US, this can be attributed to the strong relationship between LAI, and evapotranspiration, a strong parameter in the water budget (Caldwell et al., 2011). Except for the land cover factor1 (water and barren) that produced negative correlation, all other land cover types failed to have a consistent influence on the water yield. The stand age, plot disturbance, plot ownership, and silvicultural treatment drivers were significant only in a very few watersheds, which could be due to lack of data on spatial-heterogeneity of the forests (Fotheringham et al., 1996;

Dziauddin et al., 2015).

Overall our modelling approach can identify positive or negative correlations of drivers, primarily temperature and LAI, with either aboveground forest biomass or water yield. As such, these interactions can results in tradeoffs among the ecosystem services. Specifically, temperature and LAI drivers were positively correlated with biomass in some watersheds of the SE US, while negatively correlated with water yield in other watersheds. The SE US forests are likely to experience warmer temperature and indications are that this can lead to an increase in the regional drying because of high forest water use through high evapotranspiration (ET), therefore decreasing the water yield across the SE US region (McNulty et al., 2013; Sun et al., 2005).

5. Conclusion

This geostatistical analysis framework presented in this study modeled and analyzed spatially varying phenomena. We note that there are limitations in assuming a direct influence of these variables on study results. But given the availability, relevancy and common use of the FIA data for forest management purposes, we found it necessary to include in this analysis given the scope of the study. That said, the spatial characteristics of the FIA spatial characteristics will not affect such spatially-explicit analysis. However, we believe that the results of this study present a wealth of information for ecologists and natural resource and environmental scientists to study ecosystem drivers at different spatial scales and identify the drivers relevant to natural and anthropogenic changes. An additional novelty of this study is to highlight the importance of adapting a spatially-explicit model for identifying significant ecological drivers at a local and regional levels compared to traditional models that do not account for spatial variations across the landscape. We believe that such method, results, and discussions introduced in this study warrant future studies that dive into the ecological dynamics of localized ecosystem processes, which are beyond the scope of a single study such as ours.

This integrated modelling approach and use of multi-scale datasets presents a framework for better understanding the influence of ecosystem interaction drivers using available functional models (i.e. WASSI) and local spatial statistical analysis technique (e.g. Geographically Weighted Regression). Such a framework can be used to model, analyze, and map the variations in ecosystem service and process interactions at different spatial scales. Ecosystem drivers affect the services and processes differently across the spatial extent and scales. Drivers that appear to be significant at a specific location may not be significant in other ecoregions or scales. Our approach also identified common significant drivers of biomass and water yield across different watershed and ecoregion of the SE US. The significance of climate (i.e. rainfall and temperature), elevation, and LAI drivers were observed to have patterns in positive or negative correlations causing potential synergies and tradeoffs between aboveground forest biomass and water yield across the watersheds of the SE US.

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