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Inferring anthropogenic trends from satellite data for water-sustainability of US cities near artificial reservoirs

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ABSTRACT

Anthropogenic activities affect the water cycle and water supply at global and regional spatial scales, and approaches to water management must consider anthropogenic inputs. One of the major inputs in local-to-regional availability of water and the water cycle is land use land cover change as a result of urbanization, artificial reservoirs, and irrigation activity. To understand evolving trends in local hydrologic cycle for water sustainability of growing cities, this study employed a multi-factorial approach involving population trends, water use (and demand), streamflow, and various satellite-derived water-relevant variables. These variables are daily precipitation (from Tropical Rainfall Measuring Mission-TRMM, 3B42.V7), Normalized Difference Vegetation Index (NDVI) (from Moderate Resolution Imaging Spectroradiometer-MODIS-MOD13A1), land surface temperature (LST) (from MODIS-MOD11A2), and land cover (MODIS-MCD12Q1). Long term trends in such data were used to understand temporal and spatial trends in impounded watersheds hosting a large and growing city. The cities studied for water sustainability were Atlanta, Georgia and Buford dam; Columbia, South Carolina and Saluda dam; Columbus, Ohio and Alum Creek dam; Montgomery, Alabama and Jordan dam; Tulsa, Oklahoma and Keystone dam; and Tuscaloosa, Alabama and Tuscaloosa dam. Our study reveals that daily mean stream flow has been decreasing in all but one (Tulsa) of the areas selected. Satellite data trends between 2000 and 2012 showed a steady decrease in precipitation and NDVI, while LST has gradually increased. We attribute the NDVI (i.e., gradual decrease in vegetation cover) to LST rather than precipitation trends. The results of this research suggest that future temperature projections from climate models can be used in understanding vegetation activity and water availability over the study areas. Cities with larger upstream watershed area are potentially more sustainable and resilient (than those with small watersheds) as a result of spatial variability of water resources' response to climate change. Inter-basin water resources transfer is a possible solution to vulnerable cities in the future. The study results also emphasize the need to establish a sustainable and resilient water resources management system that includes narrowing the information and perception gap between the engineering community and the general public.

1. Introduction

Land use land cover (LULC) change can affect local and regional weather and climate (Mahmood et al., 2010, 2014; Kalnay and Cai, 2003; Pielke et al., 2002). The relative role of LULC change compared to other drivers is dependent on temporal and spatial scales and the geographical location. For example, a study by Zhang et al. (2007) showed the impact of human activities on precipitation from the geographical location aspect by considering different latitude bands. The trend of mean precipitation had increased in the mid-latitudes and decreased in the subtropics/tropics of the Northern Hemisphere, while the subtropics/deep tropics in the Southern Hemisphere experienced an increase. Changes in LULC are primarily responsible for change in the land-atmospheric interactions (e.g., Gibbard et al., 2005; Zhao et al., 2001). In an extended view of the changes in these interactions, the two components of water resources management – supply and demand – are affected both spatially and temporally (Schroeter et al., 2005).

There is a feedback (positive or negative) relationship between water supply/demand, population, urbanization, land use land cover change, and climate change (Fig. 1). Water supply and demand can be interpreted using socioeconomic factors and climate (e.g. Alcamo et al., 2007). However, it can be argued that water '*availability*' is prominently the driving factor for present/future '*supply*,' while '*demand*' is driven by demographic and socioeconomic factors. For irrigation alone, water withdrawal will increase by 11% (14% in developing countries and 12% in developed countries) by the year 2050 (Nachtergaele et al., 2011).

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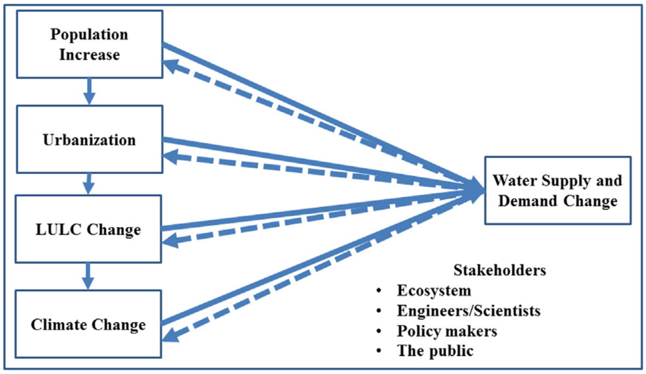

Fig. 1. Interconnection between population, land use land cover, climate, and water resources. The effect of one component on the other and hence the whole system is important for future sustainablity.

Artificial reservoirs, which are the result of dam construction, are one of the major components of LULC changes that can be drivers for irrigation practice, urbanization, and upstream inundation. Extreme precipitation and flood patterns have been known to change in impounded watersheds as a result of such LULC changes (e.g., Yigzaw et al., 2012, 2013; Yigzaw and Hossain, 2014; Woldemichael et al., 2012). This change (which can be an increase or a decrease) has also been demonstrated on probable maximum precipitation (PMP), for example by Rousseau et al. (2014), Stratz and Hossain (2014), Kunkel et al. (2013), and Woldemichael et al. (2014), using climate model results and future changes. Sustainability of water resources in the context of LULC and climate change is therefore challenging as water availability and demand are dynamically changing. A new concept of resilience and water management awareness has to be followed to alleviate the challenges to water sustainability of cities. This can be achieved through new engineering design and policy making.

Water conservation, recycled water use, conflict resolutions, and cultural changes should be part of the sustainability process (e.g., Pahl-Wostl et al., 2008; Adger et al., 2005; Tompkins and Adger, 2004; Gleick, 1998; Smit and Nasr, 1992). Bridging the gap between scientists/engineers and the public (e.g., Somerville and Hassol, 2011; McBean and Hengeveld, 2000) is also a needed area of attention as a means of achieving sustainability. One focus area of water sustainability is a city where there is a continuous increase in demand for water due to population growth (Bloom, 2011; UNPD, 2011). Future population and urban areas increase have significant impact on water and other natural resources (e.g., McDonald et al., 2014; Seto et al., 2011, 2012).

Regardless of size, artificial reservoirs play an important role in water resources management. For example, small reservoirs can supplement large scale irrigation and other water supply through rainwater

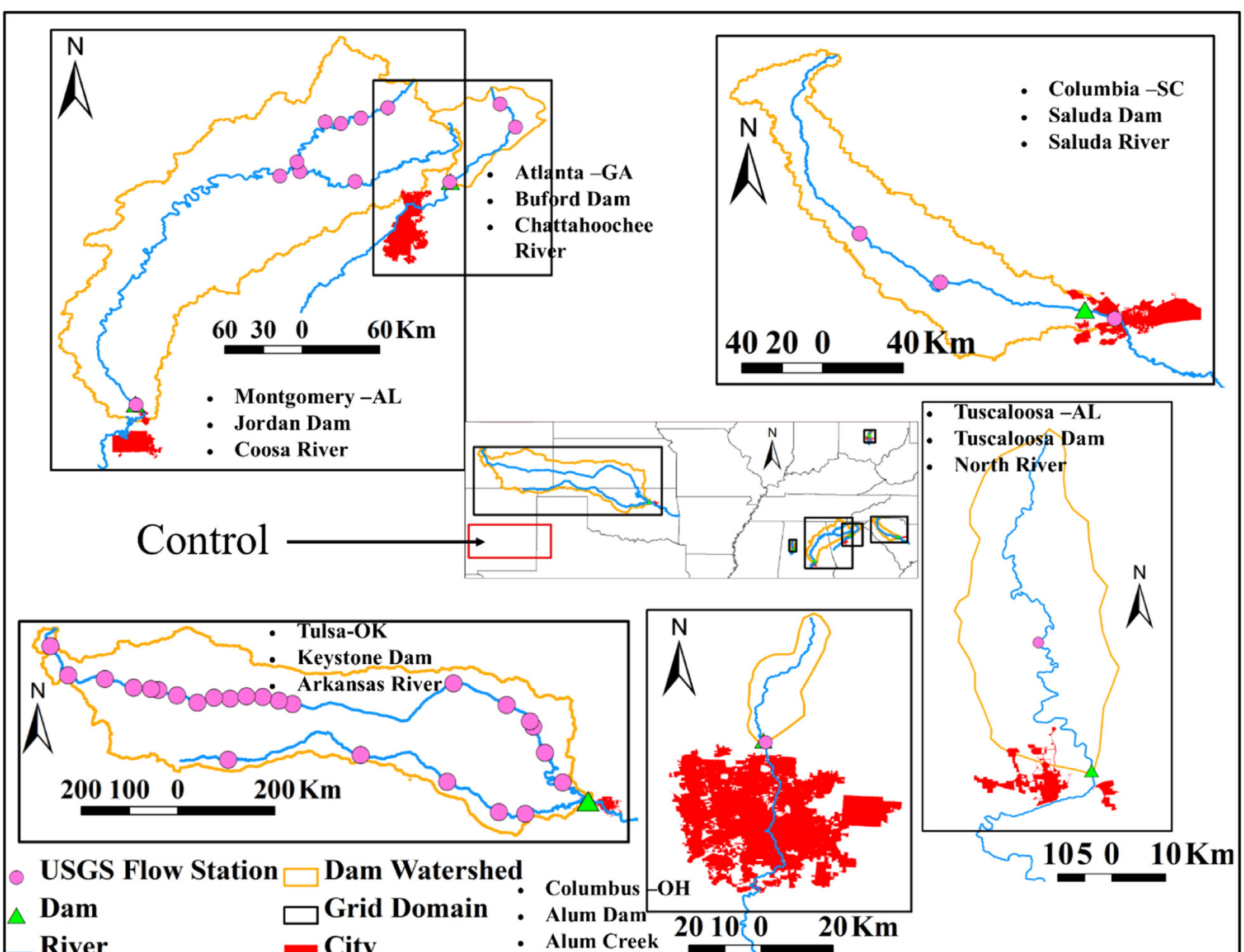

Fig. 2. Selected cities, dams, their watersheds and rectangular analysis domain.

Table 1
Selected dams' information (http://www.lakesonline.com/).

Dam	Year Constructed	Height (m)	Storage (mm^3)	Catchment area (km^2)	Purpose	Installed Power (MW)	Operator
Alum	1974	28.3	166	518	Multipurpose	NA	USACE
Buford	1956	58	3150	2693	Multipurpose	105	USACE
Jordan	1928	38	291	26,164	Multipurpose	100	Alabama Power
Keystone	1968	37	2063	192,970	Multipurpose	70	USACE
Saluda	1929	61	2700	6300	Hydropower	207	South Carolina Electric & Gas Company
Tuscaloosa	1970	38	222	1077	Water Supply	NA	City of Tuscaloosa

(USACE: U.S. Army Corps of Engineers).

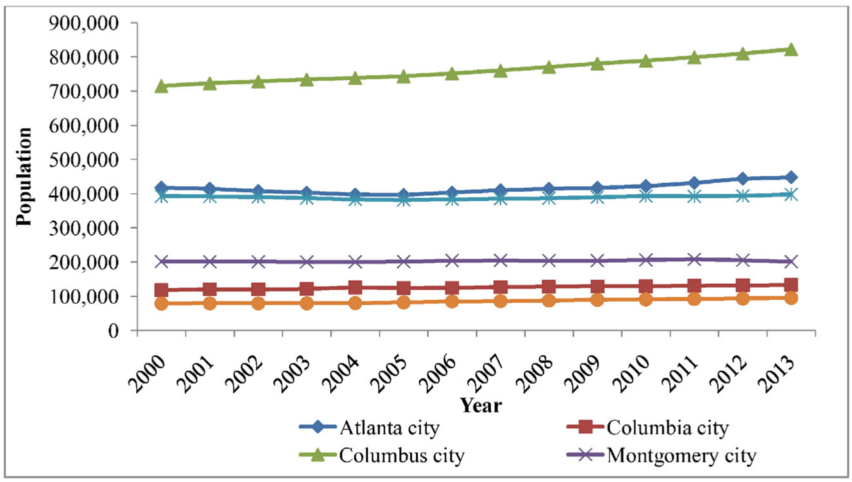

Fig. 3. Population change of selected cities from 2000 to 2012.

harvesting (Wisser et al., 2010). The pattern of artificial reservoirs use depends mostly on the level of socioeconomic development. For example, developed countries have alternate power sources (for example coal and nuclear) as compared to developing countries, where such infrastructures are a very distant vision. However, the unique contribution of power production using dams as peak-load production makes it an important component of any country's power policy, regardless of the country's development level. The potential of irrigation development is also high in developing countries, prompting construction of artificial reservoirs in the future.

There are two ways water demand can increase: (1) a direct per capita increase (McDonald et al., 2011), and (2) an indirect increase as a result of food/power production. As the population of cities increases and rural areas become urbanized, a lumped demand will result in higher water stress in the future (e.g., McDonald et al., 2014; Averyt et al., 2013; Alcamo et al., 2007; Bao and Fang, 2007; Sun and Kafatos, 2007; Vörösmarty et al., 2000; Falkenmark and Widstrand, 1992). The United Nations World Water Development Report (UNWWDR4, 2012) categorized global water scarcity under the physical category of economic water scarcity. Most of the developed countries have less water scarcity (physical and economic), while developing countries are significantly hit with economic scarcity.

Results from regional and global climatic models (RCM's and GCM's) have been used to understand how water resources will be affected in the future (e.g., Pierce et al., 2009; Sun and Kafatos, 2007). The performance of these models has improved over the course of time by means of powerful regional climate models that consider local anthropogenic impacts (e.g., Pierce et al., 2009; Christensen et al., 2007; Jacob et al., 2007). However, uncertainty still remains in selecting a specific RCM/GCM model, and a '*disconnect*' exists between apparent local physical processes and these models' results (e.g. Overpeck et al., 2011; Pielke et al., 2011; Feddema et al., 2005). One reason for this problem is the use of emission scenarios that are only virtual representations of LULC and other parameter changes relevant to a specific city in the future (Pierce et al., 2009). On a parallel note, water cycle parameters like precipitation, temperature, and vegetation are proxy to understanding water availability.

Satellite and ground remote sensing products – especially precipitation, temperature, Normalized Difference Vegetation Index (NDVI) and land cover – have been used in ecological and climatological studies in

Table 2
Metropolitan population change for selected study areas.

Metropolitan area	2010 Census	Population estimates			Percent change for metropolitan area between 2010 and 2013	Percent change for cities between 2000 and 2013
		2011	2012	2013		
Atlanta-Sandy Springs-Roswell, GA	5,286,728	5,374,678	5,457,831	5,522,942	4.5	7.26
Columbia, SC	767,598	776,793	784,745	793,779	3.41	12.78
Columbus, OH	1,901,974	1,925,137	1,944,002	1,967,066	3.42	15.06
Montgomery, AL	374,536	378,562	377,149	373,510	−0.27	−0.13
Tulsa, OK	937,478	945,386	951,880	961,561	2.57	1.31
Tuscaloosa, AL	230,162	231,560	233,389	235,628	2.37	20.84

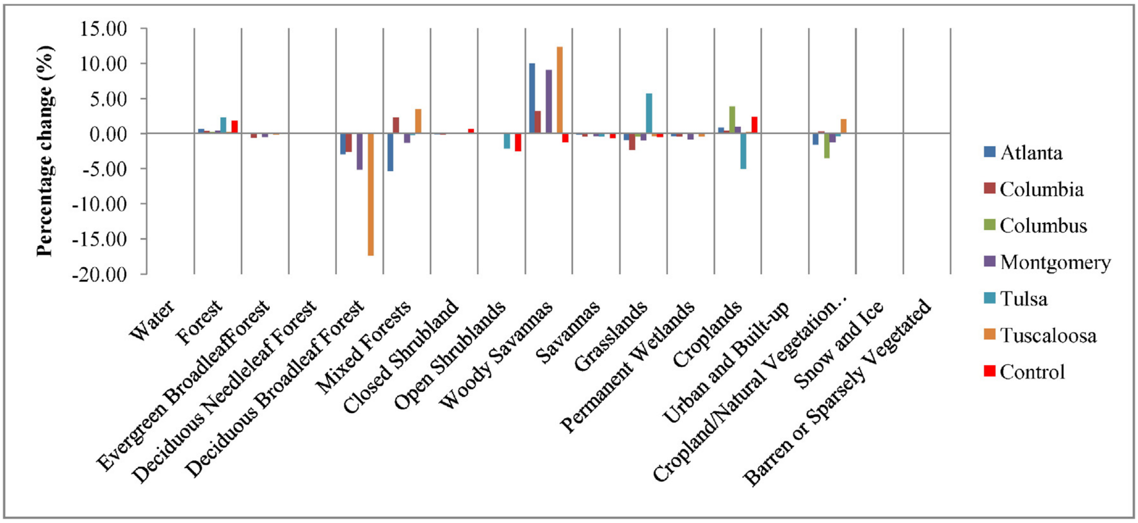

Fig. 4. Percentage change in land cover between 2000 and 2012. Negative value indicates a decrease in land use area coverage.

the wake of LULC and climate change (e.g., Yang et al., 2013; Pettorelli et al., 2005; Kaufman et al., 2002). Atmospheric and hydrological models have benefited from the spatial distribution of these products (e.g., Xue et al., 2013; Van Dijk and Renzullo, 2011). Another benefit of satellite data is spatial coverage, in which point data is deficient. As the performance of satellites improves through evolution of better algorithms and calibration, the shift from point data to spatially distributed data by leveraging the advantage of satellites is likely to become more important. Understanding the interaction between NDVI and water cycle parameters helps in understanding the impact on climate and water cycle (e.g., Zhang et al., 2013; Piao et al., 2006; Foody, 2003).

This study attempts to answer the question 'What is the trend of water use, streamflow, precipitation, temperature, NDVI, and land cover in watersheds with artificial reservoirs and downstream cities with rising populations?' The basic approach used is multifactorial, involving long records of ground, census, and satellite measurements. The study investigates long term trends over the study area using stream flow and satellite data on precipitation, land surface temperature, NDVI, and land cover. In addition, population data and water use data were analyzed to understand the implications for water management and sustainability (demand vs supply). Two more questions are also answered at the end of this study: (1) Which parameter (precipitation or temperature) can be used as a better estimator of NDVI pattern for future forecast? and (2) What is the trend direction of stream flow, population, and water usage change in the selected cities, and how well does that relate to the trends in satellite observations? The key objective of this study was to make a connection between satellite products and water resources sustainability in impounded watersheds and cities. A possible connection would support the use of satellites in the future on a local to regional scale for sustainability-driven water management practices.

2. Study area

Six cities were selected in the US based on demographic and city growth pattern, dam proximity, and spillway capacity. These cities and dams are Atlanta, Georgia and Buford Dam; Columbia, South Carolina and Saluda Dam; Columbus, Ohio and Alum Creek Dam; Montgomery, Alabama and Jordan Dam; Tulsa, Oklahoma and Keystone Dam; and Tuscaloosa, Alabama and Tuscaloosa Dam (Fig. 2). According to the National Performance of Dams Program (NPDP, 2014: http://npdp.stanford.edu), the selected dams have a high risk of failure, with inadequate spillway capacity for extreme flood events. Since satellite products (which are gridded) were part of data used in the study, grid boxes that include the selected dams' watershed and downstream city boundary were used as a study domain. In specifying the domain near the specific cities, adjacent metropolitan areas were included. This approach avoided the removal of adjacent LULC change in the form of urbanization from the study. We also selected an area where there is insignificant urbanization and water body to test the opposite hypothesis. The control area is located mostly in New Mexico and partly in Texas.

Watershed area ranged from the smallest of 518 km^2 for Alum Dam-Atlanta to the largest of 192,970 km^2 for Keystone Dam-Tulsa (Table 1). Most of the selected dams have a primary purpose of hydropower production, except for Alum and Tuscaloosa, which mainly serve for flood control and water supply (Lakes Online, 2014: http://www.lakesonline.com/). Alum Dam was built on Alum Creek in 1974 for

Table 3
Average metropolitan area water use data, in gallon per person per day (gal/p/d).

State	Metropolitan area	County water demand (gal/p/d)		
		Year		
		1985	1990	1995
Alabama	Montgomery	157	173	240
	Tuscaloosa	140	148	180
Georgia	Atlanta	170	175	196
Ohio	Columbus	142	145	146
Oklahoma	Tulsa	85	112	156
South Carolina	Columbia	113	197	163

(USGS: http://water.usgs.gov/watuse/data/).

Table 4
Total average daily water use (in million gallons per day, Mgal/d) for selected areas.

Dam	Metropolitan area	Total water use (Mgal/d)					
		1985	1990	1995	2000	2005	2010
Jordan	Montgomery	24.05	24.65	28.24	26.17	49.61	32.44
Buford	Atlanta	696.01	673.53	813.65	793.78	717.44	321.03
Saluda	Columbia	43.44	71.45	83.32	105.82	27.3	25.55
Tuscaloosa	Tuscaloosa	0.26	0.44	0.39	0.33	0.35	0.33
Alum	Columbus	251.79	163.26	163.75	204.59	181.87	177.38
Tulsa	Tulsa	671.32	813.64	791.71	912.75	844.04	409.58

(USGS: http://water.usgs.gov/watuse/data/).

flood control and to supplement the water supply for Columbus, Ohio and its metro area. Buford Dam was constructed on Chattahoochee River, creating Lake Lanier in 1956 with the main purpose of protecting the Atlanta metro area from flooding (U.S. Army Corps of Engineers-USACE, 1999). Atlanta, which is about 70 km south of Buford Dam, has experienced damaging floods as recently as 2009 and 2013. The flood damage in 2009 was estimated to be $500 million (National Oceanic and Atmospheric Administration-NOAA, 2009). Jordan Dam, which impounds Coosa River about 40 km north of the city of Montgomery, was constructed in 1928 and operated by Alabama Power for the primary

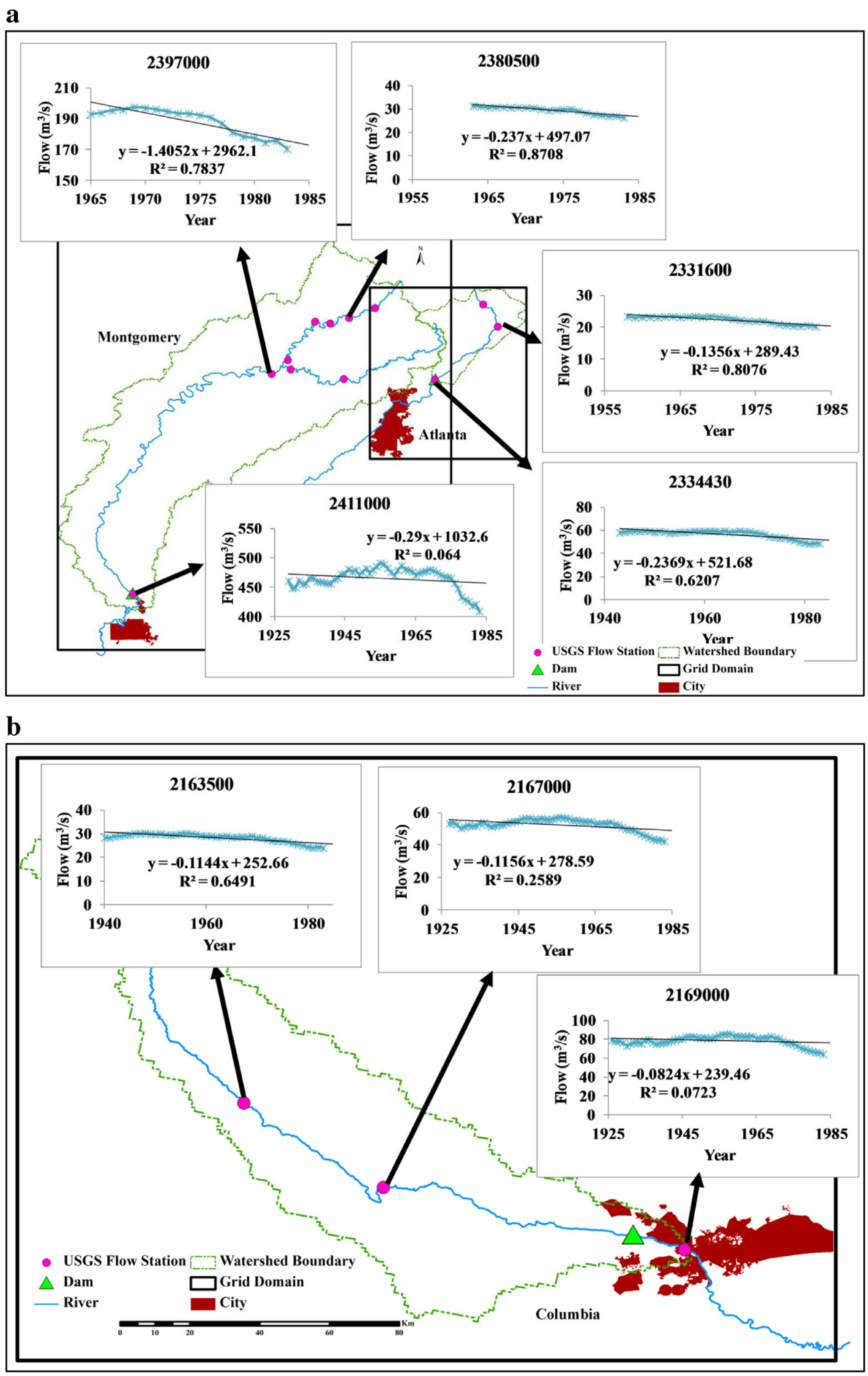

Fig. 5. a: Thirty year moving average daily flow trend for stations at Coosa and Chattahoochee Rivers. b: Thirty year moving average daily flow trend for stations at Saluda River. c: Thirty year moving average daily flow trend for stations at Alum Creek and North Rivers. d: Thirty year moving average daily flow trend for stations at Arkansas River.

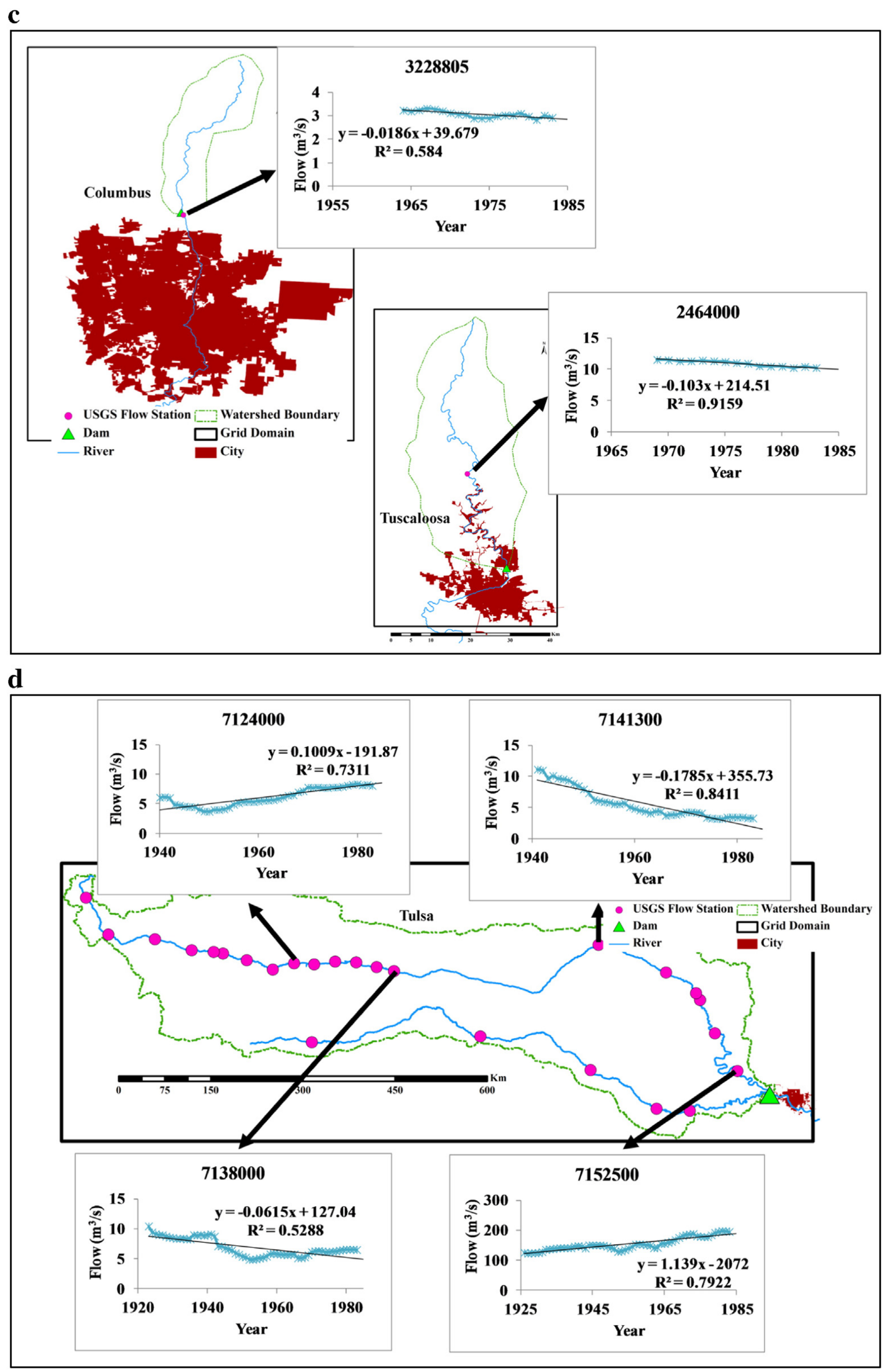

Fig. 5 (*continued*).

purposes of flood control and hydroelectric production. Keystone Dam was constructed at the confluence of Arkansas and Cimarron Rivers in 1968 as a multipurpose dam. It is located about 30 km west of Tulsa, Oklahoma. The construction of Saluda Dam in 1929 on Saluda River created Lake Murray. It is located about 15 km west of Columbia, South Carolina. The dam's primary purpose is hydropower production, with recreation and fishing as secondary benefits. Lake Tuscaloosa was created by constructing Tuscaloosa Dam on North River in 1970 so that the downstream city of Tuscaloosa, Alabama would have a domestic and industrial water supply.

The common feature of the selected dams is that their construction was triggered by increases in population and urbanization (http://www.lakesonline.com/). There are few studies available that connect the impact of these dams to local ecological process, while their impact on local and regional climate seems better studied. For example, U.S. Geological Survey (USGS) investigated the impact of Saluda Dam on water resources of the Congaree National Park Flood Plain. The result from the study showed that recurrence of peak flow had increased, while low gage heights of the Congaree River had also increased (USGS, 2008). At the same time the National Performance of Dams Program puts these dams at significant to high risk for the downstream area.

3. Data and methodology

3.1. Data

Three sets of data were used in this study: satellite, population (demographic), and streamflow data. The satellite data pertained to precipitation, land surface temperature (LST), Normalized Difference Vegetation Index (NDVI), and land cover (LC). Daily precipitation data (3B42.V7) was used at a grid scale of 0.25° and is a product of the Tropical Rainfall Measurement Mission (TRMM, 2014; Huffman et al., 2014). This data was available from 1998 to present. For this study we used the years 2000–2012. Land surface temperature (extracted from 1 km 8-Day MODIS data-MOD11A2), NDVI (extracted from 500 m 16-Day level 3 vegetation indices MODIS data-MOD13A1), and land cover (MCD12Q1) data were downloaded from NASA's Earth Observing System Data and Information System (EOSDIS) through the USGS Land Processes Distribution Achieve Center (LPDAAC, 2014-https://lpdaac.usgs.gov/) for the period of 2000–2012. Since both NDVI and land surface temperature data used in this study are level-3, the products are validated and their accuracy assessed both spatially and temporally. An 8-day

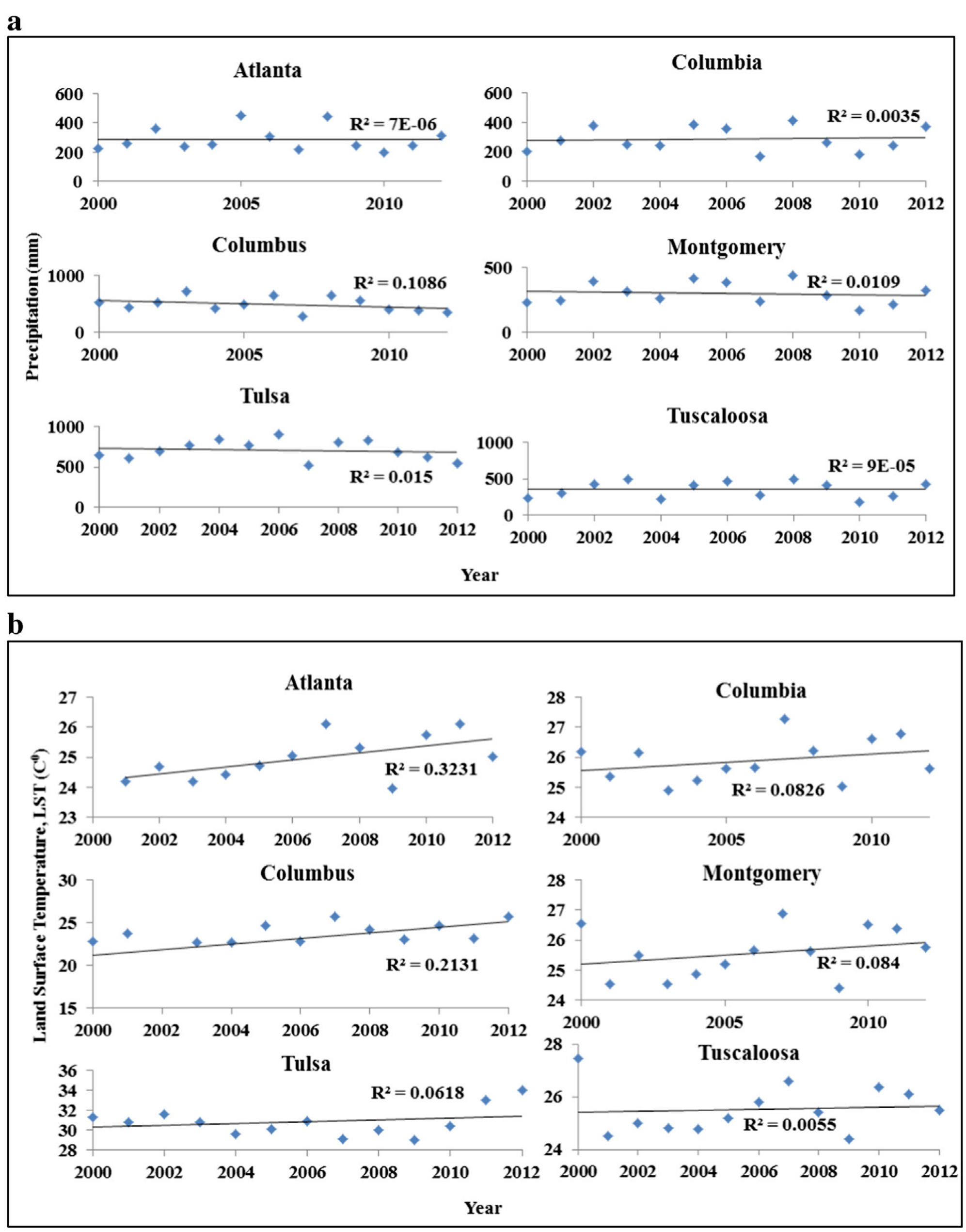

Fig. 6. a: Trend for total precipitation for growing seasons between 2000 and 2012. b: Trend for average land surface temperature for growing seasons between 2000 and 2012. c: Trend for normalized difference vegetation index (NDVI) for growing seasons between 2000 and 2012. d: Trend for precipitation, land surface temperature, and normalized difference vegetation index (NDVI) for growing seasons between 2000 and 2012.

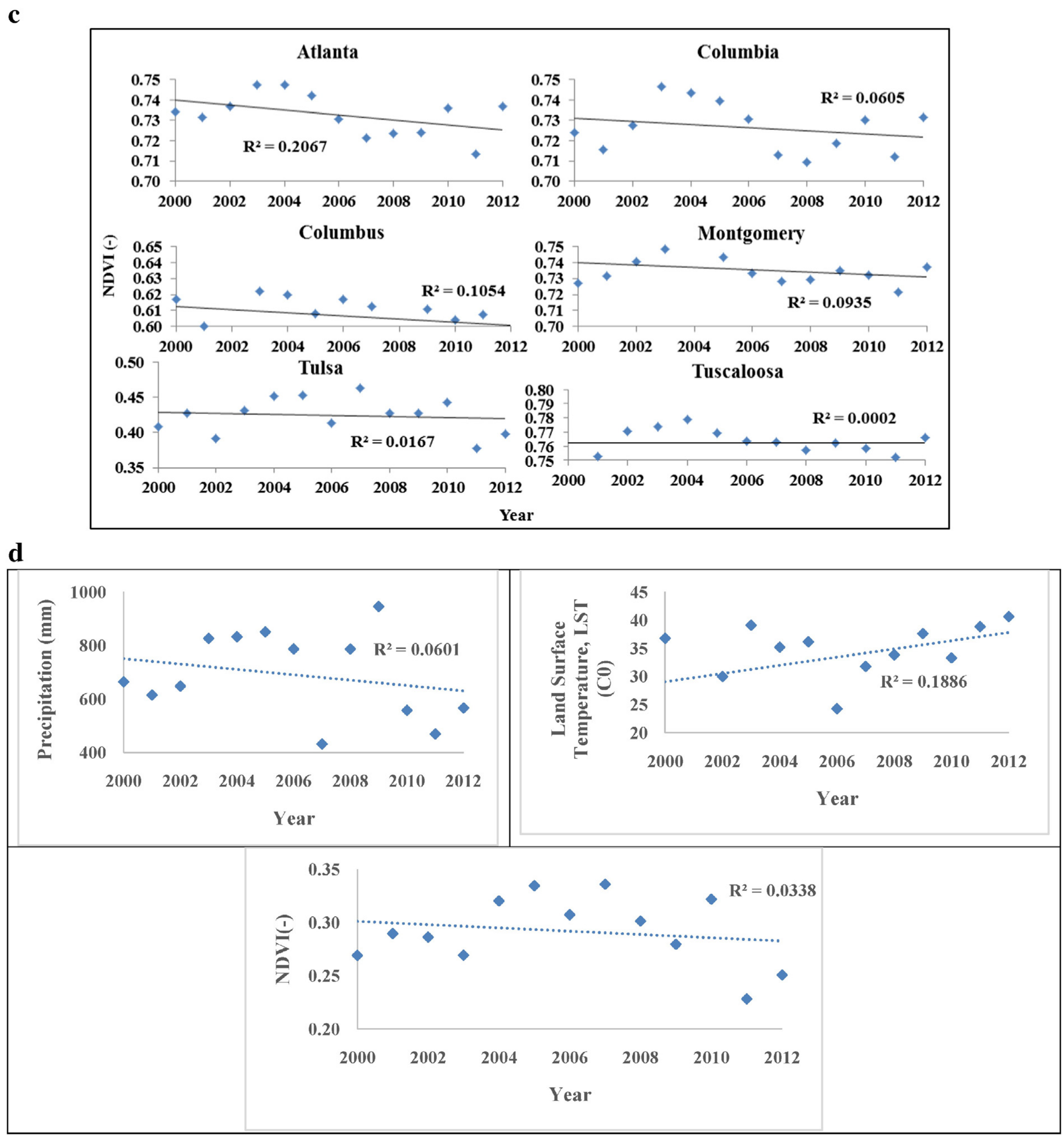

Fig. 6 (*continued*).

daytime 1 km grid land-surface temperature was used in the study. The accuracy of NDVI and temperature data are within ±0.025 and 1 K (0.5 K in most cases), respectively. Population data for the selected cites was available from the US Census Bureau (2014) (http://www.census.gov/). Water use data on a county level was downloaded from the USGS (2014b) database (http://water.usgs.gov/watuse/data/). Daily mean streamflow data was obtained from USGS (2014a) ground stations (http://nwis.waterdata.usgs.gov/nwis) to analyze the trend of flow on the rivers on which the selected dams are constructed. To obtain a more unregulated and natural 'signal' of surface water cycle parameter (stream flow), stations selected were upstream of the impounding reservoirs for all the watersheds studied.

3.2. Trend and regression analysis

The trends for daily mean streamflow were based on a thirty year moving average. The specific moving average window of thirty years was selected to achieve a smoother trend consistent with World Meteorological Organization (WMO) recommendations. Instead of calendar year (January–December), water year (October–September) was used to account for the seasonal effect in streamflow. We used trend in average of a specific land use type over a year to analyze the land cover over the selected areas. Establishing the relationship between NDVI and precipitation/temperature was the best way to understand the land-atmosphere interaction with climate and water availability. The most common approach used in analyzing NDVI is to correlate its average value with meteorological variables, average temperature, and average (total) precipitation. Given the temporal scale chosen, the apparent lag between the meteorological variables and NDVI response should be taken into consideration while correlation is done. The time-lag selection (which can be as long as a few months) depends on the availability of satellite data to cover the lag. It should be noted that NDVI values also depend on soil type. In this study two temporal scales, bi-weekly (16-days) and growing seasons

Table 5
Maximum correlation obtained ($p < 0.011$) between NDVI, precipitation, and land surface temperature (LST) for different lags for Atlanta city and Buford Dam watershed area.

Year	NDVI and precipitation		NDVI and LST	
	Correlation coeff.	Lag	Correlation coeff.	Lag
2000	0.63	1	0.73	0
2001	0.43	4	0.92	1
2002	0.38	3	0.67	2
2003	0.52	3	0.84	2
2004	0.41	2	0.86	2
2005	0.51	4	0.82	1
2006	0.84	1	0.84	1
2007	0.49	2	0.88	1
2008	0.48	1	0.86	2
2009	0.53	1	0.82	3
2010	0.44	1	0.81	2
2011	0.36	0	0.76	1
2012	0.45	2	0.8	1

(April–September), were selected for analysis as NDVI is more responsive in these temporal scales.

To analyze the relationship between NDVI and the water cycle variables, ordinary least squared (OLS) regression and geographically weighted regression (GWR) techniques were used. The use of GWR was necessary to address spatial non-stationarity (Fotheringham et al., 2003). Geographical location of an area contributes to the relationship between NDVI and precipitation/temperature. We can approach this relationship using OLS. However, it has been shown in previous studies that there is a spatial non-stationarity, which forces the use of a space based regression, for example the GWR. Eqs. (1)–(4) show expression for OLS and GWR for precipitation and land surface temperature, respectively (Foody, 2003):

$$NDVI = \beta_{0T} + \beta_1 T_{ls} + \varepsilon \tag{1}$$

$$NDVI(u,v) = \beta_{0T}(u,v) + \beta_1(u,v) T_{ls} + \varepsilon(u,v) \tag{2}$$

$$NDVI = \beta_{0P} + \beta_2 P + \varepsilon \tag{3}$$

$$NDVI(u,v) = \beta_{0P}(u,v) + \beta_2(u,v) P + \varepsilon(u,v) \tag{4}$$

Where T_{ls} is land surface temperature, and P average precipitation for a selected period, β_{0T} *and* β_{0P} are the intercept, β_1 and β_2 are slopes, and ε a residual. The (u,v) represents the location coordinates. In this study, the Spatial Statistics Tools in ArcGIS were used to estimate parameters of GWR. Satellite data for NDVI (500 m) and land surface temperature (1000 m) were aggregated to a 0.25° scale to match that of the precipitation grid resolution. The results from both OLS and GWR regressions are used as an interpretation to the spatial and temporal variation of the parameters considered. From a water management perspective, these variations are significant in understanding stationarity (or non-stationarity) between parameters, which is successively important for future forecast of water resources.

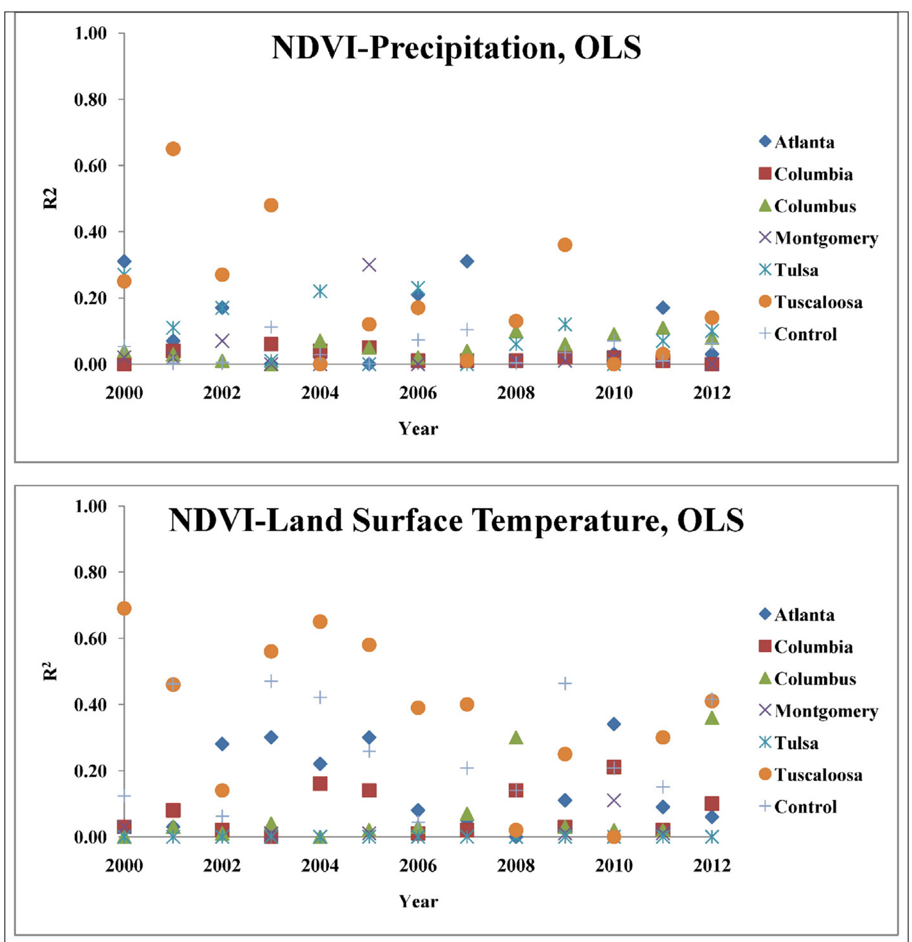

Fig. 7. R^2 value using ordinary least square (OLS) method for the period of growing season.

4. Result and discussion

4.1. Trend analysis

The first trend analysis was for population in cities and metropolitans areas. The population change for metropolitan area was between 2.5% and 4.5%, except for Montgomery which has shown a decrease in population since 2010 (Fig. 3, Table 2). For specific cities in the metropolitan area, similar trends of increase and decrease (Montgomery) were observed, except this time with greater percentage increase. Despite the decrease in population in the case of Montgomery, its inclusion in this study was attributed to its location in reference to the upstream '*high hazard*' Jordan Dam. The increases in population in the other cities were followed by changes in land cover (between 2001 and 2012) both in the metropolitan areas and upstream dam watersheds (Fig. 4). The significant land cover trend observed was the decrease in forest areas and increase in savannas. The specific impacts of these land cover changes in the process land-atmosphere interaction of the selected study areas were not explored using atmospheric models. Analysis of such impacts using atmospheric models would give spatial and temporal extent of local LULC inputs on precipitation/temperature, and hence water resources. Water bodies apparently showed no significant change between 2000 and 2012. However, this does not mean there has not been a change in the long term since the time each dam was constructed.

Analysis of water use data, which was available at a county level, showed an increase in per-capita use (Table 3) and total water use for selected cities and their metropolitan areas, except for the case of Columbia in South Carolina. The total average daily water use had also increased (Table 4). The water use data analyzed seems to have a general increasing trend; however the turning point in average daily use appeared to be the year 1995. One of the problems in analyzing water use data was the unavailability of a watershed based data. The results displayed in Tables 3 and 4 represent water use data for counties in which the selected cities and watersheds are located. In Table 4, it can be seen that there are decreasing patterns observed in the metropolitan areas, particularly after the year 1995. This is not directly related to a quantitative decrease in water use; instead it is likely attributed to the way water use data was collected. For example, for years 2005 and 2010 there was no data collected nationally for commercial, consumptive-use, and hydroelectric power.

Understanding the streamflow trend over a long period of time provides a general overview of the availability of surface water. Since the stations selected were upstream of a dam, any '*direct human influence*' on flow is non-existent. Here the direct influence refers to a streamflow change as a result of obstruction and regulation of downstream flow. Fig. 5a–c show the mean daily streamflow trend computed from a thirty year moving average window. Except for the case of Arkansas River, all rivers considered in this study resulted in a decreasing trend. Arkansas River showed a mixed trend – increase in some locations and decrease in others. It is interesting to notice that some locations in the upstream and downstream areas of the watershed indicated increasing trend, while those at the middle have a decreasing trend. The basic reason behind this could be the size of the watershed; the larger the watershed area, the higher the variability in hydrologic parameters within it.

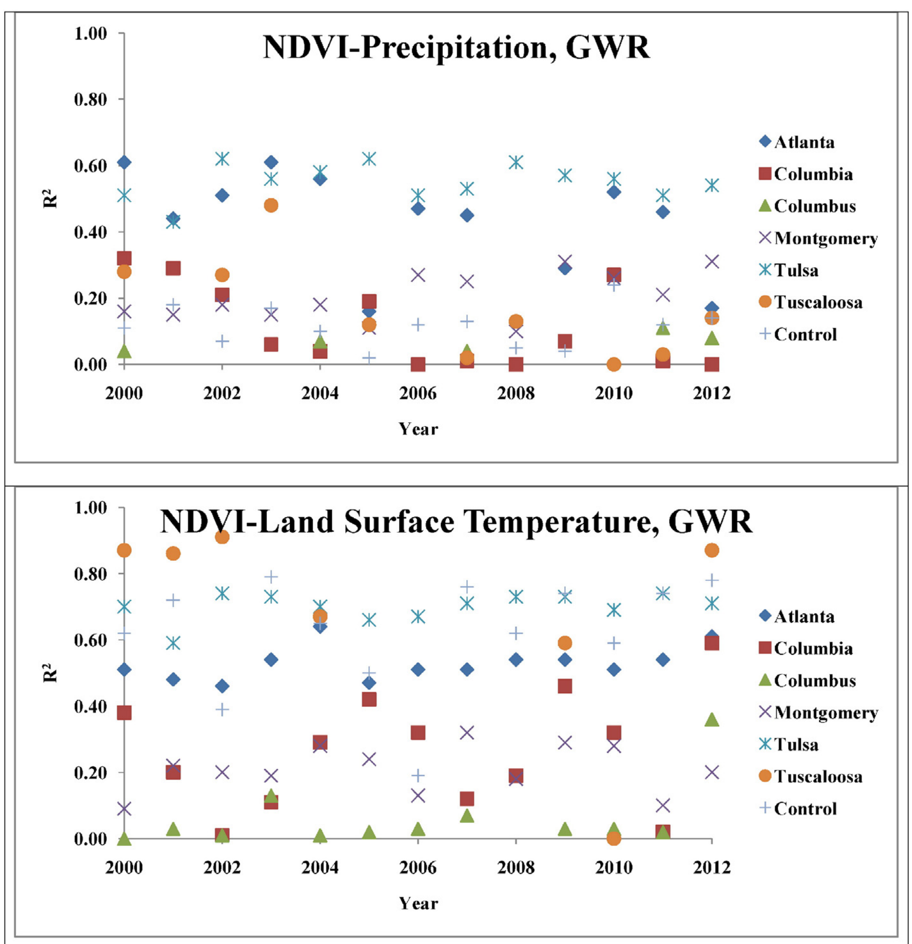

Fig. 8. R^2 value using geographically weighted regression (GWR) method for the period of growing season.

The fact that the daily mean streamflow, unlike extreme events, was decreasing overtime is a serious concern from the perspective of water resources sustainability.

Trend analyses for the precipitation, LST, and NDVI satellite data was done for 2000–2012. A change point analysis for precipitation from TRMM's daily, monthly, and annual precipitation data indicated no detectable change points, with acceptable confidence limit (> 90%). This was expected as the length of data used was too short to establish a detectable change. Therefore a simple trend analysis was done for the three satellite products. Trend analysis using a smaller temporal scale resulted in no detectable trend due to daily and monthly variability. For the daily precipitation trends, both daily mean and daily maximum were used with no difference in trend, which is 'no trend'. On the contrary, the annual precipitation resulted in a trend. For the annual time scale, a growing season was considered as a temporal window. The growing season window was selected to maximize the effect one selected parameter has on the other.

Most of the cities exhibited a decreasing trend or constant state in total annual precipitation over the growing season (Fig. 6a–c). Interestingly, the average land surface temperature trends increased over the same period. The time series data for the NDVI was analyzed by considering the average NDVI value over the domain grid. The NDVI trends indicated a decreasing pattern. The response of NDVI to temperature and precipitation is dependent on season and geographical location (e.g., Raynolds et al., 2008; Ichii et al., 2002). The opposite trends between NDVI (decreasing) and land surface temperature (increasing) is consistent with the results of Sun and Kafatos (2007), which show negative correlation between the two parameters over North American in warm seasons. As higher values in NDVI are indicative of vegetation activities, it is reasonable to say that the decreasing trends are a result of the cumulative effect of the trends of precipitation and LST in a given period. Statistically, the trends for the three satellite products might be insignificant; however, the general trend is observable given the short period data.

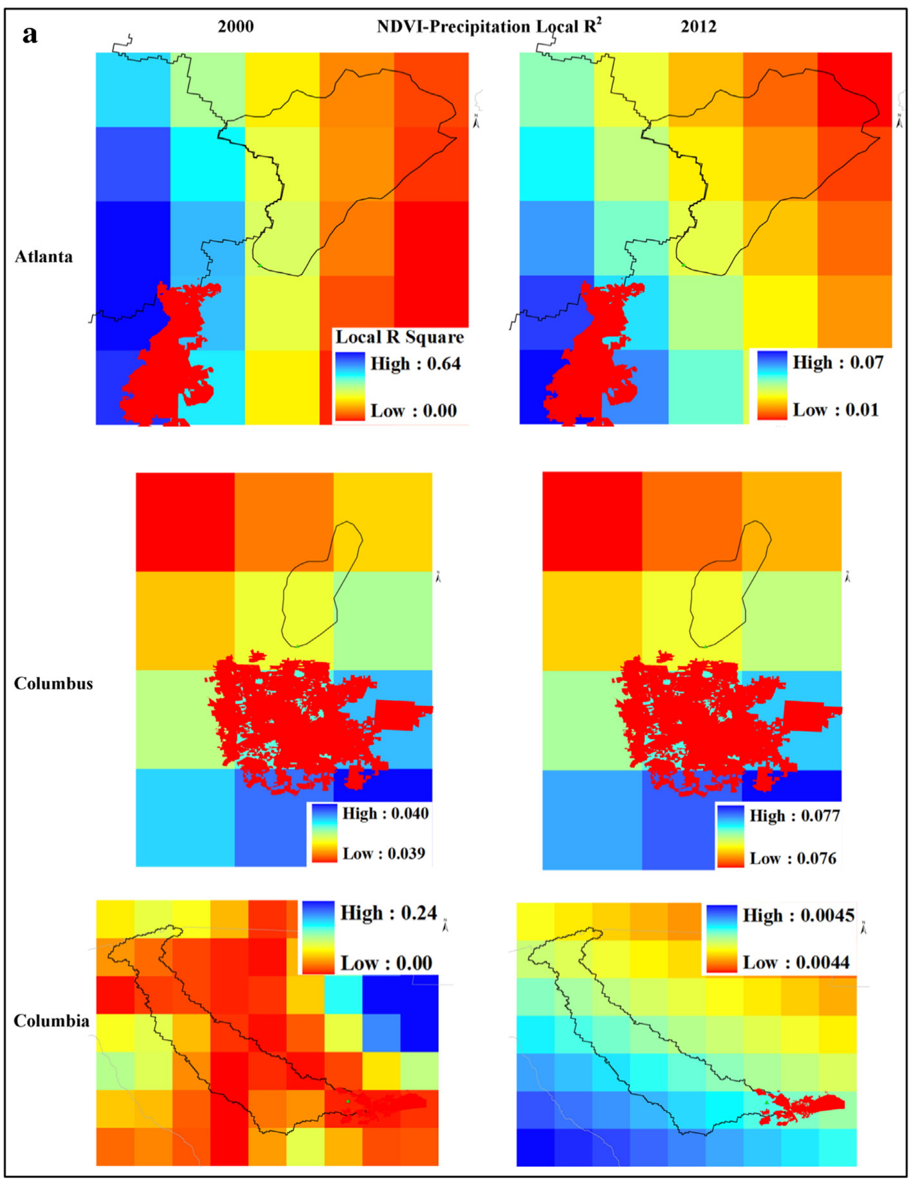

Fig. 9. a: Local R^2 calculated at 0.25° grid using geographically weighted regression for the growing season between NDVI and precipitation. b: Local R^2 calculated at 0.25° grid using geographically weighted regression for the growing season between NDVI and precipitation. c: Local R^2 calculated at 0.25° grid using geographically weighted regression for the growing season between NDVI and land surface temperature. d: Local R^2 calculated at 0.25° grid using geographically weighted regression for the growing season between NDVI and land surface temperature. e: Local R^2 calculated at 0.25° grid using geographically weighted regression for the growing season between NDVI and precipitation (upper panels) and land surface temperature (lower panels).

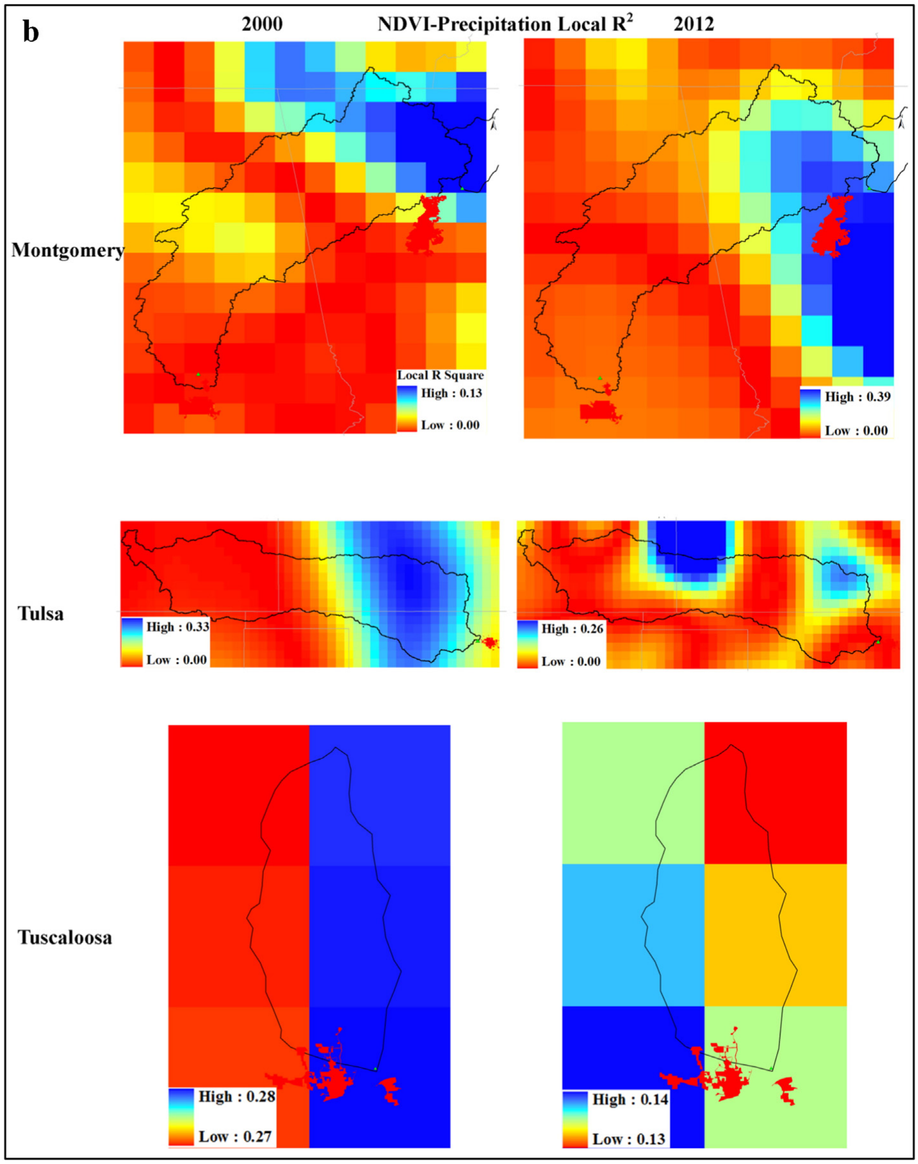

Fig. 9 (*continued*).

4.2. Regression analysis: physical cause and effect inference

The two types of regression used were ordinary least squares (OLS) and geographically weighted regression (GWR). For the case of OLS, the spatial average values of the variables in consideration are used over a selected temporal scale. This approach assumes spatial stationarity. However, for large areas where topographical and land use land cover diversity is present, GWR, which assumes spatial non-stationarity, is the best approach. The response of NDVI to precipitation and land surface temperature might not be temporally concurrent (e.g., Wang et al., 2003). Hence, it was important to look at the temporal change of NDVI by considering different time lags; that is, testing a correlation between NDVI and variable values of 0-lag (concurrent correlation), 1-lag (correlating NDVI with previous precipitation and temperature values), 2-lags (with second previous value), etc. There is a correlation between soil moisture and NDVI (e.g., Chen et al., 2014; Jamali et al., 2011; Adegoke and Carleton, 2002; Nicholson and Farrar, 1994). In this study, we argued that the correlation between land surface temperature and NDVI can be considered as a proxy for the soil moisture. This argument is based on the fact that soil moisture is affected by evapotranspiration, which is affected by temperature.

The results of NDVI maximum correlation ($p < 0.011$) for different lag periods between precipitation and temperature are shown in Table 5 (result shown for Atlanta only). Since the NDVI values used were composite, the precipitation values used represent bi-weekly (16 days) total and the land surface temperature values represent averages over the same period. The results showed best (highest) correlations were obtained on different lag period from year to year. Generalizing a temporal trend in correlation over a selected city with varying lag period results in uncertainty. As precipitation pattern varies year to year, so does its correlation with NDVI. For example, if a dry period is followed by an extreme precipitation event, the NDVI can have a quick temporal response (depending on the soil type). One more issue that became evident from the results was that NDVI is more correlated to temperature than precipitation. The use of growing season as a temporal window avoided the annual variation in lag maximizing the impacts.

The criterion of R^2 was used to compare the performance between OLS and GWR and interpret the performance of GWR. Fig. 7 summarizes the R^2 values obtained using OLS regression. Between the two regressions (NDVI-precipitation and NDVI-LST), it was evident from Fig. 7 that NDVI-LST has higher R^2 values. An interesting finding here was

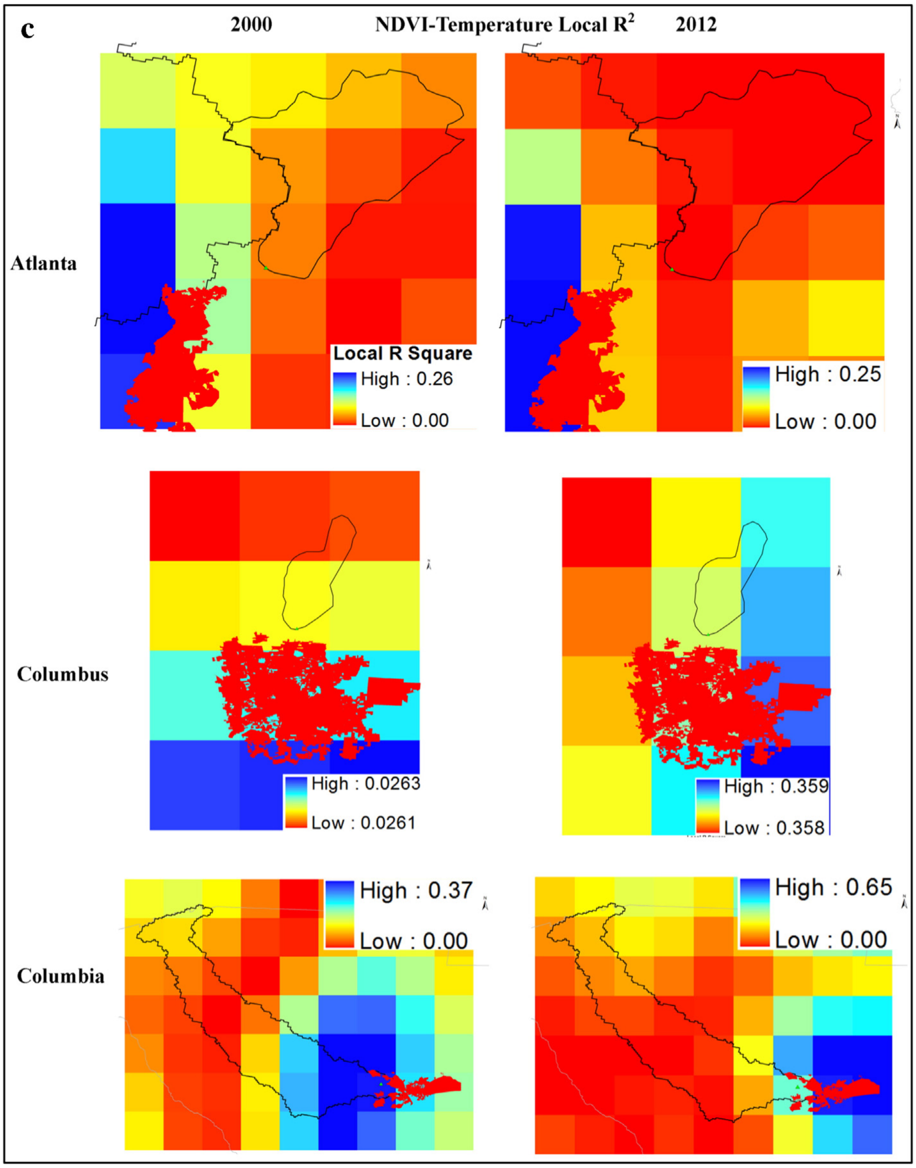

Fig. 9 (*continued*).

that, within a regression type (NDVI-precipitation or NDVI-LST), relatively better R^2 values are obtained from year to year. No distinctive correlation was observed between size of the study area and R^2 values. However, R^2 values for Tulsa and Keystone Dam watershed were higher than the others in the NDVI-LST regression, suggesting that there might be a spatial stationarity over the watershed. In Fig. 8, the R^2 values for GWR are shown. As was the case for OSL, there was a stronger R^2 value for the NDVI-LST regression than for NDVI-precipitation. This time the values in both cases were improved in some locations. However, the R^2 values were spatially distributed, as shown in Fig. 9a–d, such that in some areas the values were less than the OLS values. This was an encouraging indication regarding which regression method can be used to find a better relationship between NDVI-precipitation and NDVI-LST. According to the two regression methods implemented in this study, there is a relatively stronger relationship between NDVI and land surface temperature than between NDVI and precipitation. This means that for future projections, temperature can be considered a better estimator than precipitation for NDVI. The performances of OLS and GWR were not mutually exclusive. Therefore, in the future, a combination of both can be used on the study areas, depending on which regression method has better performance at a specific location.

The control area exhibited a general trend of decrease in precipitation and NDVI, and increase in land surface temperature over the study period. Results of regression show a better performance between NDVI and LST than between NDVI and precipitation. Geographically weighted regression showed higher R^2 as compared to ordinary least square. These results were similar in pattern to impounded and urbanized study areas considered. There are two simple explanations for this: (1) the impact of spatiotemporal (0.25° and annual) resolution used, and/or (2) the same pattern is observed for areas with the same climate region.

5. Conclusion

The primary objective of this study was to consider population, water use, streamflow, land cover, precipitation, land surface temperature, and NDVI data and analyze their trends over a long period of time to decipher the implications for water sustainability of cities. Over the study areas, a general increasing trend is observed in population, water use, and temperature, while a decrease in annual precipitation and daily mean streamflow is observed. This means a new design and policy approach should be adopted for the sustainability of water

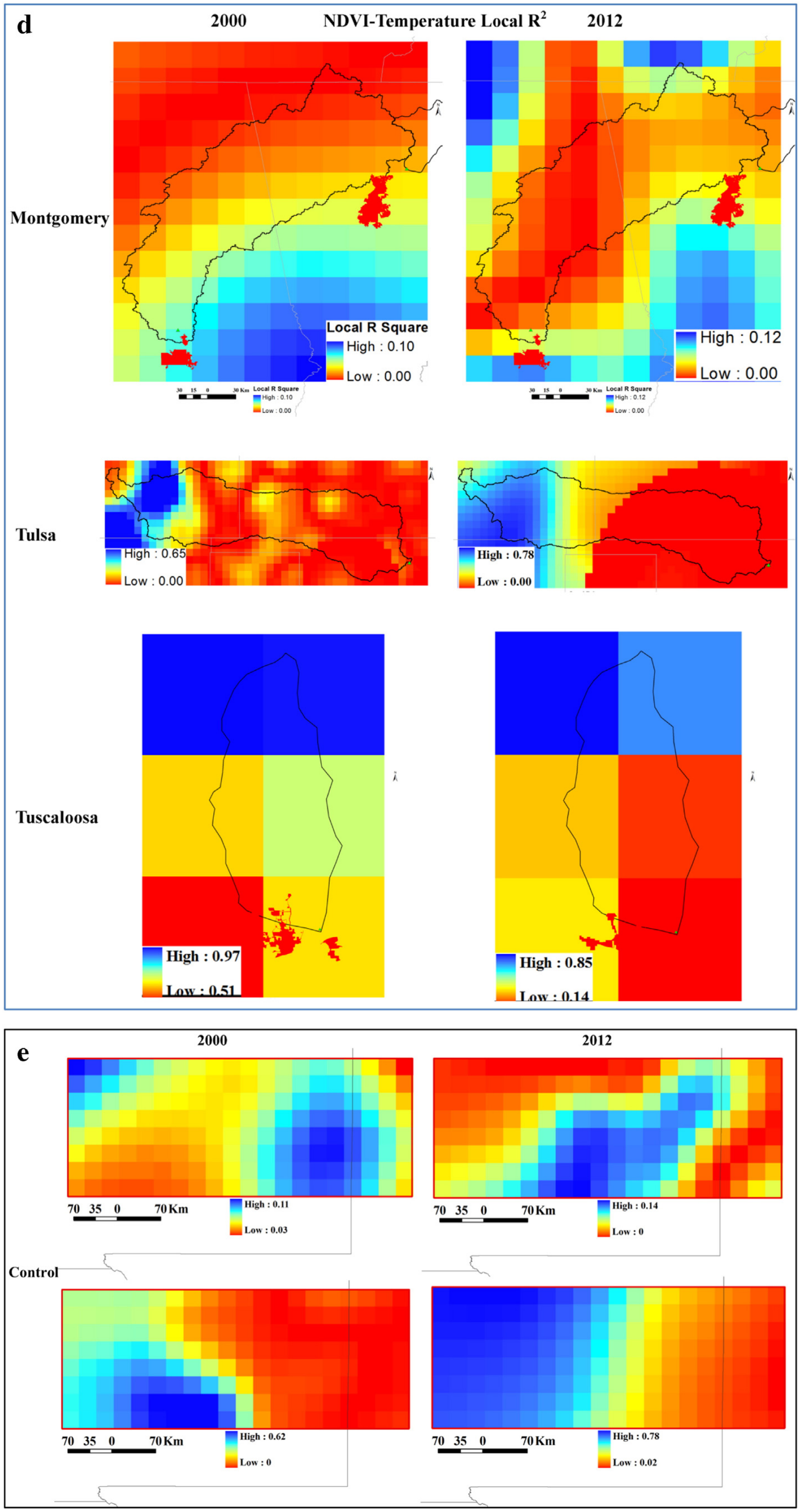

Fig. 9 (*continued*).

supply and demand. From trend analysis of the satellite data, it was evident that less vegetation activities will be the pattern in the future. This is indirectly an indication of more scarce water resources. This water scarcity may impact the ecosystem and, significantly, water availability (both surface and ground) for multiple stakeholders. Climate change, as a result of anthropogenic activities, is expressed in the form of change in temperature. Hence, the relationships established in this study are important for understanding the precipitation, vegetation, and general ecosystem patterns from future temperature projections using climate models.

The population of cities is increasing globally, with an estimated 70% of the population expected to live in cities of more than a million populations by the year 2050 (Akanda and Hossain, 2012). Consequently, this leads to increased urbanization and general land use land cover change in the future. Water resources demand will also increase, given the multipurpose requirements of drinking, power and food production, and additional public, commercial, and industrial use. Food demand is predicted to increase by 70% (Bruinsma, 2009) and hydropower by 60% (World Water Assessment Programme-WWAP, 2009) during the same year, 2050. While developed countries have better water resources management already established, developing countries are yet building large dams to manage physical and economical water resources availability. Because of hydropower's efficiency (and versatility in handling load variation), dams will continue to be part of energy policy regardless of a country's economic development. Therefore, given the large number of dams that are already constructed, under construction, and planned to be constructed, a paradigm shift in their design and operation is necessary.

The results and analyses of this research add a new perspective to future water resources management. As the availability of satellite products increases in volume and quality, a more reliable framework can be established to understand water sustainability. The use of satellite data can be a reliable and relatively less expensive approach, especially in developing countries where ground data is scarce. One can simplify the stakeholders of sustainability to be engineers/scientists, policy makers, and the general public, as well as the ecosystem that includes the water resource process. Hence, the focus of sustainability rests in the practice of design and management. One area of focus should be narrowing the knowledge and perception gap between the general public and the engineering/scientist community. This increased awareness can play an important role in the response that is required for sustainability in light of current and future climate change. What is considered the problem should be part of the solution.

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