Urban Forestry & Urban Greening 28 (2017) 81–87

Contents lists available at ScienceDirect

Urban Forestry & Urban Greening

journal homepage: www.elsevier.com/locate/ufug

Original article

Exploring the impact of green space health on runoff reduction using NDVI

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ARTICLE INFO

Keywords:
Green infrastructure
Green space
MODIS
Runoff
Texas
Urban flooding

ABSTRACT

This study examines the impact of green space health on local flooding based on the analysis of eighty-two watersheds in four Texas metropolitan statistical areas: Dallas, Houston, San Antonio, and Austin. The runoff records in October 2007 and October 2012 were selected for the assessment. The study met the methodological challenge posed by comparison by using the Normalized Difference Vegetation Index (NDVI) datasets produced based on the Moderate Resolution Imaging Spectroradiometer (MODIS) imagery of the 250-m resolution as a proxy to represent the health of green space. Two linear regression models were employed to explain the variation in mean daily runoff depth in 2007 and 2012, while controlling multiple contextual variables.Results indicate that watersheds containing healthier green spaces were likely to generate lower amounts of runoff in both periods. Standardized coefficients of green space health also show that the NDVI is a powerful and significant predictor to explain variation in runoff. These findings illustrate the important role of urban green spaces in attenuating local flooding and may provide planners and decision-makers with a method to consider, using this kind of objective greenery index in further developing local and regional green infrastructure and land-use plans.

1. Introduction

The world's urban population has increased by approximately 423% from 1950 to 2014 (United Nations, 2014). In the United States, about 82.5% of the population resided in urban areas in 2014, and its percentage is expected to increase to more than 89% by 2050 (United Nations, 2014). The increasing urban population has increased demand for space in expanding urbanized areas, which has often brought about negative consequences in natural environments. Rapid urbanization has contributed to replacing existing natural green spaces with impervious surfaces (Booth et al., 2002; Kim et al., 2016a,b,c). The alteration of undeveloped lands affects the function of watersheds directly or indirectly by changing the rate/volume of surface runoff and the frequency/severity of storm events (US Environmental Protection Agency (USEPA), 2009). In response to these growing impacts of urbanization on hydrological process, flooding has become the most significant and frequent disaster among 633 urban areas worldwide (United Nations, 2012).

Previous studies have documented benefits of urban green spaces. Urban green spaces contribute to improving community members' physical and mental health (Hartig et al., 1991; Kaplan and Kaplan, 2003; Kim et al., 2014; Kim et al., 2016c; Ulrich et al., 1991), and increasing economic values of the neighborhood (Kim et al., 2016a,b,c; Li et al., 2015; Morancho, 2003; Sander et al., 2010; Tyrväinen, 1997). Various ecological benefits of urban green spaces include air and water pollution mitigation, and land surface temperature reduction (Alberti, 2005; Chen et al., 2014; Connors et al., 2013; Li et al., 2012; Nowak and Greenfield, 2012).

In addition, the effect of green spaces upon surface runoff has been widely explored in previous studies applying various measurements (e.g., field survey, lab experimentation, and modeling). Zhang et al. (2015) investigated how the changes of landscape pattern influence overall runoff in Beijing, China, from 2000 to 2010, by employing 2.5-m resolution images. The findings demonstrated that landscape patches of green space decreased continuously during the study period and the reduction ratio of rainwater runoff declined from 23 to 17%, consequently.Liu et al. (2014) assessed the impact of green infrastructure on urban flooding reduction through a simulation model and found that the storm runoff volume can be reduced by 15% when an integrated green infrastructure system is employed. Sterling et al.

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http://dx.doi.org/10.1016/j.ufug.2017.10.010
Received 6 January 2017; Received in revised form 24 July 2017; Accepted 13 October 2017
Available online 18 October 2017

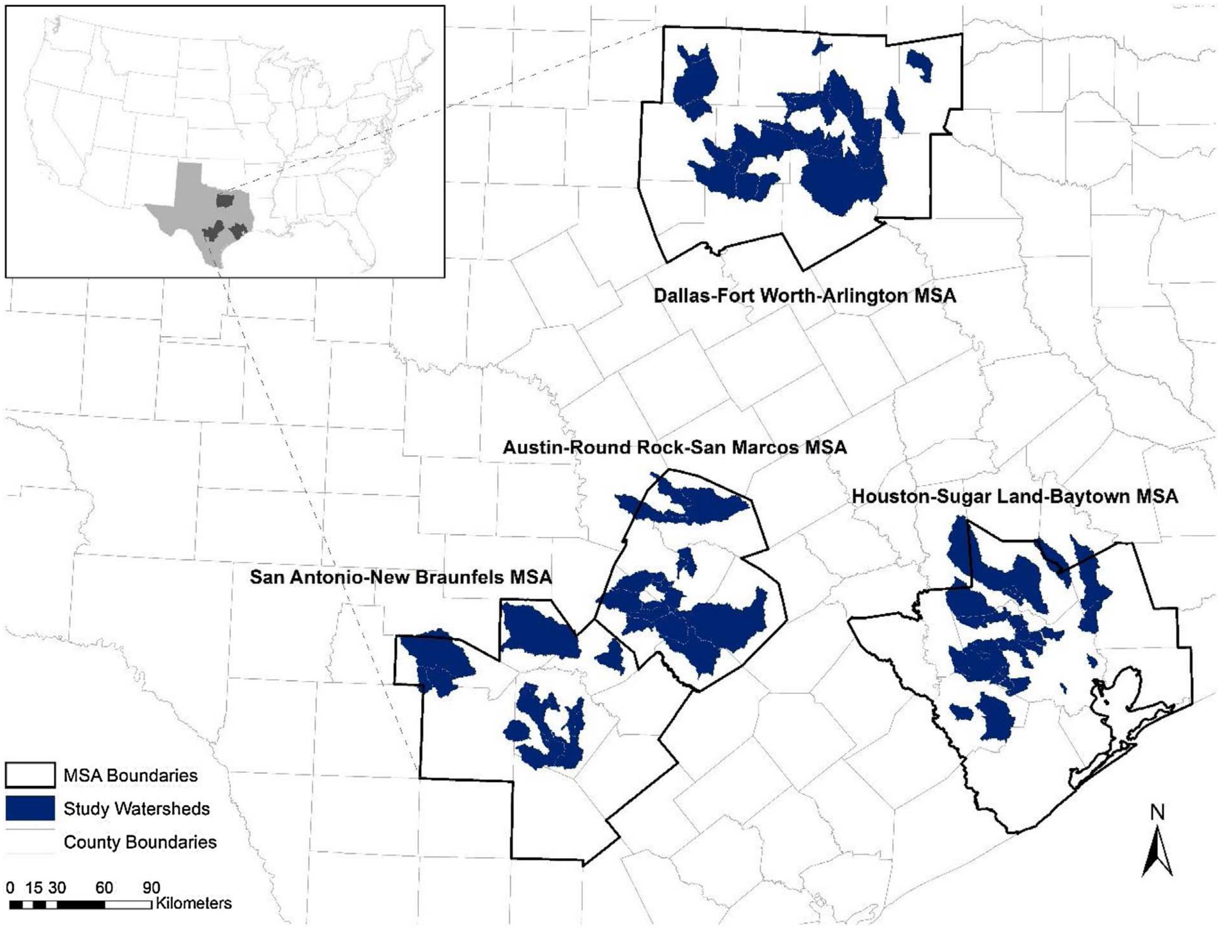

Fig. 1. Four MSAs and the selected watersheds.

(2012) examined the relationship between global land cover change and runoff increment through land surface model (LSM) simulations. They discovered that the reduction of forests and grasslands was one of the largest factors that increased runoff (projecting 6.8% of increment between 1950 and 2000). In general, land cover change through urban development increased the surface runoff or streamflow as the proportion of impervious surfaces increased (Arnold and Gibbons, 1996; Fox et al., 2012; Kim and Li, 2016; Walsh et al., 2005). Thus, protecting as well as maintaining healthy green spaces will be an important matter for the future development. There is no clear definition of what a healthy green space is. Typically, however, it is often described as an ecosystem that is productive, diverse, sustainable, and resistible to stress through time (Rapport, 1992; Tzoulas et al., 2007). This study used Normalized Difference Vegetation Index (NDVI), based on spectral reflectance in the red and near-infrared regions, as an indicator of "greenness" or relevant amount of green biomass for a certain geographic area (Gamon et al., 1995).

Although several studies have used land cover data in estimating runoff generation, more empirical studies will be necessary to quantitatively measure the impact of the healthiness of green spaces on runoff reduction in urban areas. A few previous studies have attempted to objectively examine the relationship between stormwater runoff volume and urban green spaces using NDVI. Particularly, classified land cover images and NDVI satellite imageries were heavily used from previous studies to estimate the value of green areas. NDVI, however, has been shown to better correlate with tree canopy cover rather than other land covers (Li et al., 2015). NDVI has been adopted by previous studies as a proxy for representing the productivity of vegetation and describing the condition of urban green spaces (Jenerette et al., 2011; Kahya et al., 2010; MacDonald et al., 2010; Mansfield et al., 2005; Odindi and Mhangara, 2012; Rafiee et al., 2009). Higher NDVI scores indicate larger green biomass and healthier vegetation status. Since the watershed plays an important role in determining the characteristics of hydrology pattern, including the amount of runoff, understanding how green spaces are structured at the watershed-level will provide planners a better guideline in conserving and developing future green spaces.

In various disciplines, researchers used NDVI to quantify the influence of urban green spaces on urban heat island effects (Mackey et al., 2012; Wilson et al., 2003), property values (Payton et al., 2008; Li et al., 2015), and obesity prevention (Bell et al., 2008; Liu et al., 2007). In addition, NDVI has been adopted in previous studies to map impervious cover (Knight and Voth, 2011) and identify spatial patterns of phosphorus forms in Stormwater Treatment Areas (STA) (Corstanje et al., 2016). The use of NDVI affords tremendous potential to expand the scope of current literature by advancing the measurement of green space health and assessing the impact of green space health on stormwater runoff.

The present study evaluates the efficacy of green spaces in urbanized areas on runoff reduction in four of the largest Metropolitan Statistical Areas (MSAs) in Texas, USA: Dallas, Houston, San Antonio, and Austin. Specifically, this research seeks to identify whether the health of urban green space could be a strong predictor to explain the variation of surface runoff. At the outset, we hypothesized that mean runoff depth would be negatively associated with the green space health while controlling for key factors related to runoff generation.

The next section introduces the background of the study area, sample collection, concept measurement, and assessment methods. Section 3 reports the results. Section 4 discusses the findings and provides concluding remarks.

2. Material and methods

2.1. Study areas and sample selection

The population growth rate of Texas was 9.24% from 2010 to 2015, which ranked in the top three fastest growing states in the U.S. (US Census, 2015). Particularly, the population of four Texas MSAs together increased by more than 400,000 between 2014 and 2015, which was the highest growth rate among all other MSAs in the U.S. (US Census, 2016). Due to those rapid population growth rates, the land consumption rate on the outskirts of those urban areas has increased significantly (Ewing and Hamidi, 2014; The Brookings Institution, 2016). A substantial amount of green areas has been converted into impervious surface and thus instigated more urban flooding events. Among the four largest MSAs in Texas ranked by population – Dallas-Fort Worth-Arlington, Houston-Sugar Land-Baytown, San Antonio-New Braunfels, and Austin-Round Rock-San Marcos – we selected specific watersheds that were delineated from the U.S. Geological Survey (USGS)'s gauge stations. Among 195 USGS gauge stations within each of the MSA boundaries, watersheds were delineated where a gauge station had runoff records for October 2007 and October 2012. Even if gauge stations had the records, if the delineated watersheds did not overlap with the MSA boundary by more than 50% they were excluded. A total of 82 sample watersheds were finally chosen for this study (see Fig. 1).

The average annual precipitation of the regions was about 994 mm (39.13 inches) from 2000 to 2015, and the highest month was October with an average monthly rainfall of 116.3 mm (4.58 inches; Texas Water Development Board (TWDB), 2017). The median sample watershed size was 159.9 7 km^2.

2.2. Research design

2.2.1. Dependent variable

The dependent variable, average daily peak runoff depth, was measured from the streamflow record of 82 USGS gauge stations for October 2007 and October 2012. To normalize and control the size of watersheds, runoff depth (mm) was used for this study rather than adopting the streamflow (m^3/s). Runoff depth was calculated through the following equation (Eq. (1)), in order to convert the unit from cubic meter per second to millimeter.

$$\text{Run off Depth (mm)} \frac{\text{Streamflow (m}^3\text{/s)}}{\text{Watershed Size (m}^2\text{)}} \times 86,400\ \text{(s)} \times 1,000\ \text{(mm/m)} \quad (1)$$

Runoff depth has been commonly used by the USGS for its estimation of mean and peak runoff volume (Kim and Li, 2016). Mean daily peak runoff depth was 210.08 mm in 2007 and 42.45 mm in 2012. Due to the distribution of the runoff depth, which was positively skewed, the dependent variable was log-transformed before running statistical analysis.

2.2.2. Independent variables

NDVI, an index for the health of green spaces, is one of the most commonly used indices to compute values of VI. NDVI is used by many researchers to conduct studies between vegetation conditions and other environmental variables. NDVI is calculated by the difference between near infrared and red band values then divided by the sum of near infrared and red band values based on a per-pixel basis of a remote sensing image. Fig. 2 shows the example of an aerial photo and NDVI in a specific watershed.

For this research, NDVI is one of the most important independent variables in the final models. Based on previous studies, we selected the NDVI datasets produced based on the Moderate Resolution Imaging Spectroradiometer (MODIS) imagery of the 250 m resolution. The datasets based on 30 m Landset were not selected as they were not available before the year of 2013.

In this study, NDVI data were collected through the Global Agriculture Monitoring (GLAM) Project (Becker-Reshef et al., 2010)

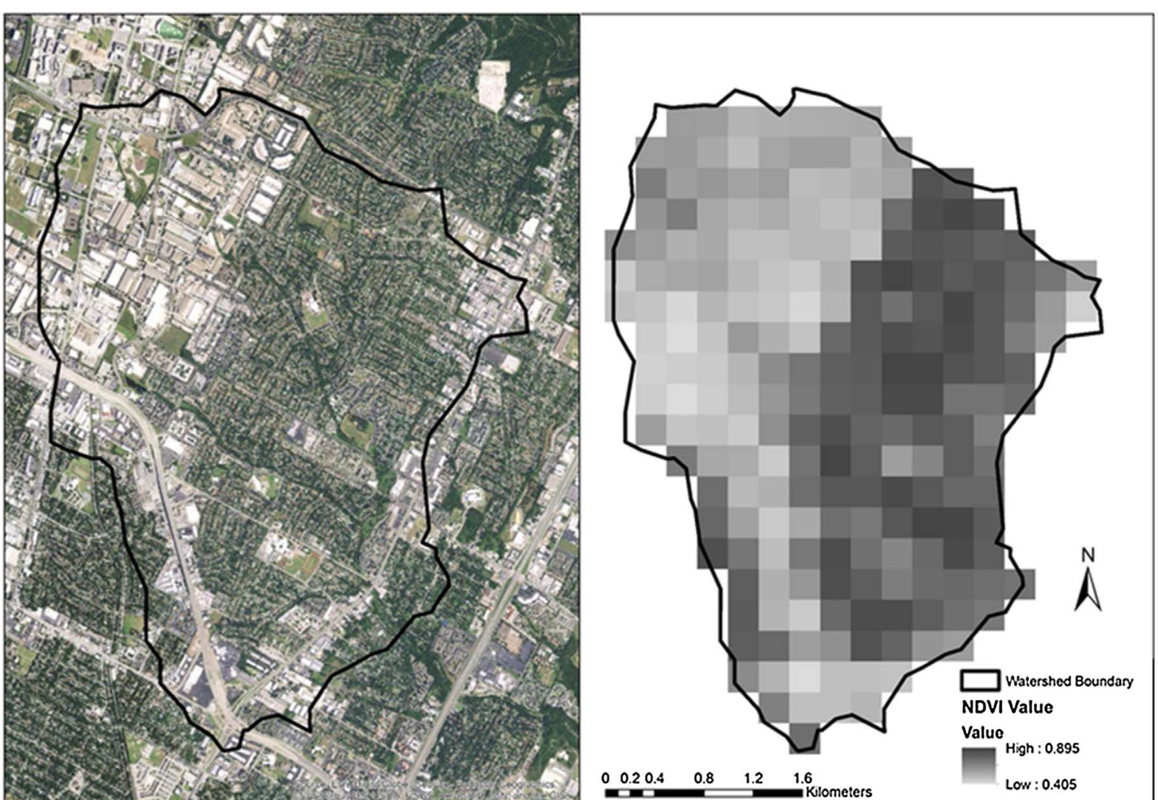

Fig. 2. Example of an aerial photo and NDVI in a specific watershed.

based on the National Aeronautics and Space Administration's (NASA's) flagship instrument MODIS imagery. The GLAM NDVI data are provided in the interval of 16 days with a 250 m spatial resolution in the format of a raster image and available from 2000 to present.

Based on the GLAM database for the study area, by diminishing the utility of certain time series images due to cloud and cloud shadow contamination, October was considered as the most appropriate time for using the NDVI images to calculate greenness of the selected watersheds. This time of season also had the highest average monthly rainfall as well as runoff. Thus, we used the average NDVI values of October in the years 2007 and 2012.

Contextual control variables that are known to influence surface runoff have been measured, which are a mixture of biophysical, basin characteristic, and geographical factors. First, four variables are included in the biophysical factors: average precipitation, soil porosity, drainage density, and the percentage of 100-year floodplain. Precipitation is commonly known as the strongest predictor of surface runoff (Brody et al., 2013). More amounts of rainfall will result in more volumes of runoff. Average precipitation for October 2007 and October 2012 were obtained from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) Climate Group, which uses the climatologically-aided interpolation (CAI) method in producing the surface precipitation record. Soil permeability generally relates with the infiltration capacity and affects overall volume and frequency of runoff during the storm events (Chang and Franczyk, 2008).

The porosity of soil was measured and analyzed using the State Soil Geographical Database (STATSGO). Drainage density, a ratio of total stream length to watershed area, is often employed to identify the hydrologic responses of a landscape (Berger and Entekhabi, 2001). Because streams that are highly cut apart tend to respond promptly to rainfall, watersheds with higher drainage density will generate more amounts of runoff (Bell, 2004; Horton, 1932). Hydrography data derived by the United States Department of Agriculture (USDA) were used in ArcGIS to calculate this ratio. The 100-year floodplain indicates a 1% chance of inundation in each year for a certain area, and it has been used as a one of key markers of flood risk (Brody et al., 2013). Considering its impact on flood occurrence, we computed the percentage of floodplain for each sample watershed with the data acquired from the Federal Emergency Management Agency (FEMA) Map Service Center.

Second, runoff may also differ from the basin parameters. Watersheds that have steeper slopes and are more elongated tend to produce more runoff. Both mean slope and the elongation ratio (basin shape) were calculated using 30 m resolution digital elevation models (DEMs) from the National Hydrography Dataset (NHD) Plus Version 2.

Finally, two geographical factors (impervious cover and wetland) that may directly or indirectly affect surface runoff were included as control variables in this study's statistical model. Impervious surfaces have been shown from numerous studies to exacerbate the volume, frequency, and magnitude of stream flow (Arnold and Gibbons, 1996; Braden and Johnston, 2004; Paul and Meyer, 2001). In contrast, natural wetlands have been demonstrated to reduce and mitigate rainfall runoff (Bullock and Acreman, 2003; Highfield and Brody, 2006). Impervious cover was measured by calculating the proportional areas of developed lands that were previously classified in the USGS's National Land Cover Database (NLCD; land cover code from 21 to 24). The percentage of wetlands was computed by including woody wetlands and emergent herbaceous wetlands that were classified as land cover code 90 and 95, respectively, in the NLCD. Table 1 summarizes the measures of each variable.

2.3. Data analysis

This research used ordinary least squares (OLS) regression analysis to explain the variation in mean daily runoff depths. Due to the limited data availability for various control variables, we were able to gather data for the full list of variables only for two years: 2007 and 2012. We decided to employ the cross-sectional analysis in which our modeling work is conducted separately for 2007 and 2012. For each year, we regress the log of the runoff amount over NDVI and the control variables based on the OLS estimator. An alternative to our analytical approach would be to calculate differences from 2007 to 2012 for all variables and assess how the change of NDVI (2012 vs. 2007) influences the change of the runoff amount based on the same OLS regression framework. However, a major shortcoming of such an alternative is that the change in runoff might be due to some endogenous climatic factors which influence both the runoff and the NDVI. Considering these possibilities, we have analyzed two models separately with the dependent variables of average runoff depth for two periods, while controlling the same set of variables that are specified in the above section. Through the diagnostic processes, we ensured that any of our statistical assumptions (e.g., model specification, multicollinearity, heteroscedasticity, outliers, and spatial autocorrelations) were not violated.

Table 1
Research construct.

Variable	Measurement	Source; Analytical tool	Range	Mean	S.D.
Independent variable					
Green space health (NDVI)	Average NDVI values in October 2007	GLAM; ArcGIS	0.38–0.78	0.54	0.07
	Average NDVI values in October 2012		0.36–0.72	0.52	0.08
Dependent variable					
Mean runoff depth (log-transformed)	Average daily runoff (mm) at each USGS gauge station in October 2007, divided by watershed size	USGS Gauge Stations, ArcGIS	0.21–3.48	1.49	0.85
	Average daily runoff (mm) at each USGS gauge station in October 2012, divided by watershed size		0.04–2.72	1.00	0.76
Control variables					
Precipitation	Mean annual rainfall in October 2007; units in mm	PRISM Climate Group	11.06–150.31	66.99	39.14
	Mean annual rainfall in October 2012; units in mm		14.34–82.25	31.63	15.41
Slope	Average watershed slope; units in percentages	USEPA – NDHPlus V2	0.13–11.64	1.99	2.19
Shape	Elongation ratio	USEPA – NDHPlus V2	1.42–26.26	7.41	4.14
Soil permeability	Average watershed soil permeability; units in inches per hour	NRCS – STATSGO	0.10–4.88	1.18	0.93
Floodplain area	Area within the FEMA-defined 100-year floodplain; units in percentages	FEMA Flood Map Service Center	4.25–46.72	15.79	9.76
Natural drainage density	Ratio of total stream length to basin area	USDA	0.21–2.01	0.61	0.25
Impervious surface	Proportion of impervious surface in 2006; units in percentages	NLCD	0.11–44.00	14.46	11.22
	Proportion of impervious surface in 2011; units in percentages		0.50–99.96	43.20	33.93
Wetland	Proportion of wetland in 2006; units in percentages	NLCD	0–5.95	1.71	1.65
	Proportion of wetland in 2011; units in percentages		0–20.29	2.92	4.05

3. Results

As Table 3 illustrates, population in all four Texas MSA increased significantly, by 23.5–37.3%, from 2000 to 2010. However, population-weighted density, which refers to the average density of the census tracts within the MSA, shows dissimilar growth rates for each metropolitan area (US Census, 2013). Dallas, Houston, and Austin MSAs had negative values, while San Antonio MSA had a positive rate during the same period. This indirectly indicates that Houston, Dallas, and Austin MSAs are growing rapidly, but land developments are occurring more significantly near the suburbs. San Antonio MSA data only showed that developments are concentrated at higher density areas. Although the number of sample watersheds differs by MSA, we could consequently identify that median runoff of watersheds within Dallas and Houston MSAs generated more runoff compared to San Antonio ones. Watersheds within Austin MSA, however, produced relatively less runoff than San Antonio MSA. We may possibly expect the reason is because: 1) several sample watersheds were located outside the inner city area for the Austin MSA, 2) impervious surfaces were fairly low compared to other MSAs, or 3) impacts of Austin's strict watershed protection regulations that were mainly to protect Edwards Aquifer, which is the principal drinking water source of Austin and nearby areas.

Table 2 shows regression results with the OLS model. The variance of NDVI, along with the control variables, could explain 29% of the variance in the runoff. Keeping other variables constant, a one-unit increase in NDVI would reduce the runoff amount by 2.7% in the 2007 model; such an effect is highly significant. A number of control variables have a significant impact on the runoff. In the 2007 model, as expected, a 1% increase in the overall slope and the impervious area would significantly increase the runoff of a watershed by 14.3% and 2.1%, respectively. However, the increase of wetland area had an opposite association with the runoff. In the 2012 model, a 1% increase in the elongation ratio (watershed shape), the impervious area, and wetland area would show significantly positive relationships be increasing the runoff amount of a watershed by 3.9%, 1.3%, and 3.8%, respectively. For every 1 millimeter increase in annual rainfall, the runoff of a watershed would significantly increase by 0.8% in the 2007 model, while it would increase by 1.3% increment in the 2012 model. The runoff impact seems positive for soil permeability, natural drainage density, and floodplain coverage; however, none of these effects is statistically significant according to our model.

Our modeling results for 2012 are consistent with those from 2007 regarding signs of impact for NDVI and the control variables. The 2012 model seems to achieve a higher modeling performance, as the variation in NDVI and the control variables could explain 50% of the variance of the runoff amount (compared to 29% for the year of 2007). The 2012 model reveals that an increase in precipitation, the impervious area, or the wetland areas would significantly increase runoff in the watershed; such findings are consistent with the 2007 model. However, it is worth noting that according to the 2012 model, a one-unit increase in NDVI would decrease the runoff amount by 1.3 %; such an effect is only half of what was estimated by the 2007 model; with a higher standard error, such an effect was significant only at the 0.1 level.

Standardized beta coefficients were presented to determine which specific variables most influence the degree of average runoff. In 2007, NDVI was the most powerful predictor in explaining the variance in runoff, followed by slope, precipitation, wetland, and impervious area. In 2012, however, impervious surface was the most significant predictor, followed by NDVI, precipitation, basin shape, wetland area, and floodplain.

4. Discussion and conclusions

Impervious surfaces in urban areas have been proven to increase stormwater runoff, which enlarges the vulnerability to more frequent flooding events, and compromises the environmental health of streams and rivers in watersheds (Arnold and Gibbons, 1996; Brabec, 2009; Yao et al., 2015). Urban green spaces play a significant role in controlling stormwater runoff and bringing other benefits to the community such as ecological, social, health, and economic benefits (Kaplan and Kaplan, 2003; Kim et al., 2014; Li et al., 2012; Nowak and Greenfield, 2012; Sander et al., 2010). Our research has contributed to literature by documenting the watershed-level evidence about the benefits of green spaces in retaining runoff water. We found that healthier green spaces contribute to reduced runoff amounts. Our findings are consistent with previous studies (Kim and Park, 2017; Nourani et al., 2017) about the physiological mechanisms of vegetation to retain and cleanse runoff water.

Since rapid urbanization has been considered one of the major issues in the US cities, understanding ecological functions of urban green spaces has been stressed in many previous studies (Forman, 1995; Forman and Gordon, 1986; Turner, 1989). They have documented less fragmented, larger, and well connected green spaces could contribute in creating ecological healthy conditions (Dramstad et al., 1996; Forman, 1995). The reciprocal interrelationships between development demands and the ecological quality of natural environments should be

Table 2
Regression results.

Variables		2007 Model (D.V.: Mean daily runoff depth in October 2007)			2012 Model (D.V.: Mean daily runoff depth in October 2012)		
		Coefficient	Standard error	Beta coefficient	Coefficient	Standard error	Beta coefficient
Green space health	NDVI	−0.0272***	0.0099	−0.4665	−0.0134*	0.0068	−0.2857
Biophysical characteristics	Precipitation	0.0076***	0.0027	0.3483	0.0129**	0.0049	0.2612
	Soil	0.0868	0.1172	0.0946	0.0136	0.1002	0.0165
	Drainage density	0.2370	0.3729	0.0684	0.2005	0.2658	0.0647
	Floodplain	0.0151	0.0123	0.1733	0.0156*	0.0092	0.1998
Basin characteristics	Shape	0.0298	0.0235	0.1447	0.0392**	0.0166	0.2131
	Slope	0.1432***	0.0505	0.3686	0.0600	0.0361	0.1729
Geographical characteristics	Impervious surface	0.0206**	0.0103	0.2710	0.0127***	0.0026	0.5672
	Wetland	0.1407*	0.0714	0.2721	0.0381*	0.0223	0.2023
Constant		3.7250**	1.5725		1.1926	1.0941	
F ratio		4.64			10.05		
Probability > F		0.0001			0.0000		
Adj. R^2		0.2881			0.5014		
Root MSE		0.7195			0.538		

Note: N = 82.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

Table 3
Descriptive statistics.

	Dallas MSA	Houston MSA	San Antonio MSA	Austin MSA
Number of watersheds	23	27	13	19
Average watershed size (km^2)	285.97	196.83	315.05	245.13
Population change from 2000 to 2010 (%)	23.45	26.11	25.17	37.33
Population weighted density change from 2000 to 2010 (%)	−3.77	−9.4	2.06	−0.06
Median daily runoff depth in 2007 (mm)	57.21	41.45	19.92	4.18
Median daily runoff depth in 2012 (mm)	19.95	22.47	9.99	0.84

investigated to recognize the benefits of urban green spaces to respond to the current urbanization issues. To assess the ecological quality of green spaces, quantifying the natural environment brought many challenges due to its complexity, temporal and spatial scales and data availability.

For this study, we analyzed NDVI values from MODIS data to capture a proxy of green spaces' ecological health conditions since the values reflect the amount of green area. MODIS NDVI data provide advantages in large study areas such as a citywide, statewide, and regional level (Knight and Voth, 2011). Our final models indicated healthy green spaces would positively contribute in decreasing surface runoff in the selected metropolitan areas. However, comparing 2007 and 2012 models, we could discover that the beta coefficient of NDVI significantly decreased in 2012 model. We may not directly compare two models, but this result possibly elaborates that the portion of green spaces is rapidly decreasing within the study area, and thus, protection of green spaces should be more carefully considered at the local and regional level. In addition, the increment of impervious surfaces is suggesting that analyzing the development patterns in the future could better explain the variation of runoff as metropolitan areas are continuously expanding in a rapid pace.

Understanding ecological functions of urban green spaces has been emphasized to respond to climate change issues. During the past decades, extreme weather events hit cities in the U.S. and internationally at an unprecedented rate, contributing to socio-economic damages. A consensus is forming that resilient urban infrastructure systems are urgently needed to adapt to climate changes. Urban green spaces serve as a critical green infrastructure component to the functioning of urban ecosystem services; however, their benefits and importance have not been fully understood by policy makers. The growing understanding of how green spaces may benefit communities and ecosystem services has increasingly encouraged localities to adopt green infrastructure planning (Lynch, 2016). Specifically, local land-use decisions are known to be one of the most significant factors that disturb watersheds and result in landscape fragmentation (Brody, 2003). Planners and policy makers are thus highly encouraged to embrace green space health indices when developing land-use strategies and ordinances. Informed land use planning may minimize rainfall runoff and conserve the overall ecosystem, and produce economic and social co-benefits. At regional levels, state green infrastructure programs and initiatives as well as watershed management plans should better incorporate ecological planning.

This study has several limitations. To develop more accurate estimation models, the finer resolution of NDVI datasets should be considered for smaller scale of study areas. According to Vaze et al. (2010), the accuracy and resolution of the input raster data should be carefully considered as they influence the values of important spatial indices. Yang et al. (2014) suggested that the optimal resolution for LiDAR (Light Detection And Ranging) generated by DEM for large watershed hydrological modeling was 10 m. However, they further suggested that finer resolution may not be feasible for environmental modeling as the modeling instrument had not been upgraded to use datasets at higher resolutions. In addition, we used the 250 m resolution MODIS NDVI data from the GLAM database; even though some previous studies claim that these data are preprocessed to control for improving quality of imagery with a less cloud cover problem, our NDVI data were not completely cloud-free. Finally, this study used several variables suggested by previous studies relevant to watershed runoff. Based on the between-watershed variance in the cross-sectional data, we estimated the runoff impact of green spaces. When multiple years of climate and geospatial data become available, future researchers may conduct panel data analysis, which models multiple years of observations for each watershed simultaneously. The panel data analysis allows researchers to control for watersheds' time-invariant characteristics (e.g. socioeconomic capitals, political settings, and various geospatial features that are difficult to quantify) and better illuminate the impact of urban green space health on runoff.

Despite those limitations, the findings from this study may serve as guidelines to create green hubs at the subdivision level and may help regional agencies to identify and focus on strategic areas for linking these hubs. Future researcher may expand this study by calculating the direct and indirect costs and benefits associated with projects aimed to enhance the health of green spaces.

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