

Applying fuzzy logic to open data for sustainable development decision-making: a case study of the planned city Amaravati

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Abstract The Indian State of Andhra Pradesh is in the process of designing and constructing a planned capital city on the southern banks of the Krishna River at Amaravati. This region will see a significant increase in urban land cover and impervious surface area (ISA) under the 2050 draft perspective plan from the Andhra Pradesh Capital Region Development Authority. As the city central zone sits on the former floodplain of the Krishna River and is subject to concentrated rainfall during monsoon seasons—this increase in ISA risks increasing flood risk through preventing infiltration of storm water and causing increased peak storm water flow (NRSC 2014). The State has announced plans for a “zero-flooding city” through implementation of technologies including green roofs, porous pavement, and detention ponds (ADC 2017). This study aims to facilitate these efforts through mapping of present and future land usage, regional flood risk, and environmental services utilizing open-source data in order to maximize efficiency of installed green infrastructure and minimize future flood damages. A map of relative soil infiltration capacity was created through fuzzy overlay of sand percentage, clay percentage, and bulk density at several depths. Relative flood risk maps for both present-day land cover and a 2050 scenario were developed using several factors: elevation, flow accumulation, surface runoff, and soil properties. A novel Relative Environmental Services Provided Index is proposed here to in order to encourage cost-effective and ecologically sound development through composite visualization of carbon storage, greenery, runoff coefficients, and soil flood prevention.

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1 Introduction

Sustainable development is crucial for India as it seeks to meet goals set in the Paris Climate Agreement as well as their United Nations Sustainable Development Goal (SDG) commitments. The Paris Agreement went into effect in November 2016 with a goal of limiting global temperature increases to 1.5 °C above pre-industrial levels. According to the World Bank (2013), rising temperatures threaten to reduce India's crop yields, cause regional droughts, and intensify seasonal monsoons. While India has committed to generating 40% of electricity from renewable sources by 2030, many other sources contribute to greenhouse gas emission. For example, expanding urban development releases carbon formally sequestered in forests or cropland. Soil carbon levels under impervious surfaces are generally lower than in agricultural and forested lands, and previous studies have also shown that urban greenspaces partially offset carbon sequestration losses, but these also demand increased usage of fossil fuels, fertilizer, and water (Yan et al. 2016). In their submission to the Paris Agreement, India also acknowledges the importance of forests in carbon storage, citing programs such as the Green India Mission and Compensatory Afforestation—which provides funding to States to finance reforestation (UNFCCC 2015).

Through the United Nations SDGs, India has committed to ensuring sustainable use and conservation of forests, wetlands, drylands, and freshwater ecosystems as well as halting biodiversity loss and incorporating these values into planning and development fully by 2020. A National Institute for Transforming India report (2016a, b)—focusing on SDG #11 regarding sustainable cities and communities—suggests that high priority should be given to “participatory land use policy” empowered by land use maps of planned development in order to “facilitate conservation and management of forests, biodiversity and ecosystem services” at a village level. Although approaching land use mapping at a regional level, this study seeks to utilize land use mapping to better inform both citizens and planners in accordance with achieving these United Nations goals.

The environmental consequences of urbanization are wide ranging and include: decreased water quality, increased flood risk, reduced carbon sequestration, and loss of habitat (Bardhan et al. 2011, 2015, 2016). Nevertheless, urban populations are rapidly growing, with two-thirds of the global population projected to live in cities by 2050 (Wang et al. 2017). India is a prime example of rapid urban population growth. From 2001 to 2011, the population of India's urban centers increased by 31.8%, while populations in rural areas increased by only 12.2% (Chandramouli 2011). The large increases in urban population have placed stress on infrastructure and the environment, especially evident in current state of physical infrastructure such as drinking water and storm water management systems. Urban areas in India are often burdened by poor drinking water distribution, low pipe pressures, intermittent supply, and low-quality water (IMUD 2011; Jana et al. 2016). Unplanned development and increasing impermeability of surfaces have increased the peak discharge from storm events, overloading poorly maintained drainage capacity, causing flooding. From 2000 to 2010, impervious surface area in India as a whole increased by 2274.62 km² (Wang et al. 2017).

The Andhra Pradesh Reorganization Act of 2014 bifurcated Andhra Pradesh to create the State of Telangana with Hyderabad, the former capital of Andhra Pradesh, as its

capital. In 2015, Andhra Pradesh chose Amaravati as the location of a new planned capital city. APCRDA projects a population of 3.55 million in Amaravati by 2050, comparable to contemporary Berlin (ADC 2017). This rapid urbanization makes Amaravati an interesting case study and presents an opportunity to illustrate how environmental services such as flood prevention and carbon sequestration can be best incorporated in the development of the city to support quality of life and environmental sustainability. This study seeks to provide environmental context to support intelligent development in the Amaravati region to and sustainable future environmental services. Therefore, a new index—relative environmental services provided (RESPI)—is proposed here to illustrate these services through a fuzzy overlay of relative soil infiltration capacity, surface runoff, carbon sequestration, and primary production—approximated via the normalized difference vegetation index (NDVI).

2 Related literature

Several case studies have revealed the effects of urban area expansion on climate change (Wang et al. 2017; Yan et al. 2016; Nagendra et al. 2013), biodiversity (Nagendra et al. 2013), air quality (Kishtawal et al. 2010), heavy rainfall (Kishtawal et al. 2010; Pielke et al. 2007), and water availability and quality (Nagendra et al. 2013). The myriad environmental and social effects of urbanization necessitate thoughtful development and can be alleviated through the incorporation of geospatial datasets into urban planning (Bardhan 2017; Bardhan et al. 2011, 2015). Building upon the following findings in the geospatial analysis discipline, this study seeks to illustrate how rapid urbanization in Amaravati will affect carbon storage and flood risk. The outputs will inform development strategies to minimize flood risk and maximize environmental services.

Bardhan (2017) and Bardhan et al. (2016) stressed that coherent use of geospatial data sets with the geospatial analytics can bridge the gap between the disciplines of climate planning and urban planning. She demonstrated that flood risk analysis can be performed in an input–output blackbox tool using spatial analysis principles. This tool can then be used by urban planners, who are less acquainted with the climate planning language, to derive risk maps that can aid in planning process. Yan et al. (2016) used Landsat TM (Thematic mapper) data and land classification to deduce changes in carbon storage over a 20-year period in Urumqi, China, and found a 19% reduction in stored carbon due to the displacement of bare land and cropland by increased Impervious Surface Area (ISA) of low carbon intensity. They also found that this increased ISA resulted in less continuous and more fragmented greenspaces, which holds ecological consequences by limiting the movement of native plants and animals to urban islands.

Kishtawal et al. (2010) utilized satellite rainfall data to identify a positive correlation between heavier monsoon rainfalls and urban cover. This effect was linked to the urban heat-island induction of low-level convergence as well as increased aerosol loadings resulting in cloud formation (Pielke et al. 2007). They found that the mean seasonal monsoon rainfall in India has not shifted dramatically as a result of climate change. However, extreme rainfall events over 120 mm/day have become increasingly common over the last 50 years—of particular concern for storm water collection systems. The study also referenced the Metropolitan Meteorological Experiment—which took place in the United States in the 1970s—which found urban effects account for a 5–25% increase in precipitation, most evident 50–75 km downwind from the urban center. A review by Pielke et al. (2007)

finds higher precipitation over urban areas and downwind areas, as well as correlation to heavier rainfall events.

In their assessment of urbanization impact in India, Nagendra et al. (2013) concluded that population increase and urban sprawl in India have cascading effects on ecosystem services and biodiversity. They noted increased flood risk for coastal and riparian regions, with uneven burdens falling upon those of lower socioeconomic classes. They also mentioned the case of Mumbai, where infilling of tidal flats and destruction of mangroves have increased flood risk. This is relevant to Amaravati, which is being constructed on a floodplain of the Krishna River. Potential solutions include maintenance of vegetative buffer along water bodies and implementation of rainwater detention and infiltration systems—subject to local soil properties. This study provides regional guidance on optimal placement of such green infrastructure systems.

Wang et al. (2017) developed impervious surface area (ISA) maps of the whole of India from 2000 to 2010 utilizing Landsat data. They found that ISA changes during this time period were localized in regions seeing large population growth such as New Delhi and Mumbai and were correlated with increases in gross state domestic product. During this decade in Andhra Pradesh, there was a 55.32 km² increase in ISA. Zope et al. (2017) linked increases in built-up land to increased peak runoff discharge in the Poisar River basin in Mumbai, India—although they demonstrated that installation of detention basins significantly reduced this effect. The future expansion of ISA and population in Amaravati suggests both increased flood risk and environmental stress. It is imperative that the city minimize development of areas with high environmental services such as forests and land with high rainwater infiltration capacity and utilizes green infrastructure to ensure sustainable growth. Hence, an index that captures the cumulative environmental services available in the region, and can potentially be vulnerable to threats from the proposed development, is a necessary inventory for sustainable development. An index is an aggregate of disparate elements that summarize the impact of those elements collectively (Banzhaf and Boyd 2012). Here the environmental service index is intended as a measure of quantity that relates to the total value of nature, whether enjoyed directly by people or used by people as inputs, without quantifying it directly (Fisher et al. 2009). Such single index of environmental services would serve policymakers as a useful performance indicator and a benchmark for assessing status of environment-related well-being.

3 Materials and methods

3.1 Study area

Figure 1 illustrates the selected study area for this study—covering a 3892 km² region that includes the existing urban centers of Vijayawada and Guntur and is split by the Krishna River. The area consists largely of agricultural and bare lands with forests located primarily at higher elevations in the north. The central zone of the planned capital Amaravati will sit across the Krishna from Vijayawada, as shown in the APCRDA development plan shown in Fig. 2. Under this plan, the region will see a major increase in urban and industrial land cover at the expense of primarily bare and arable land.

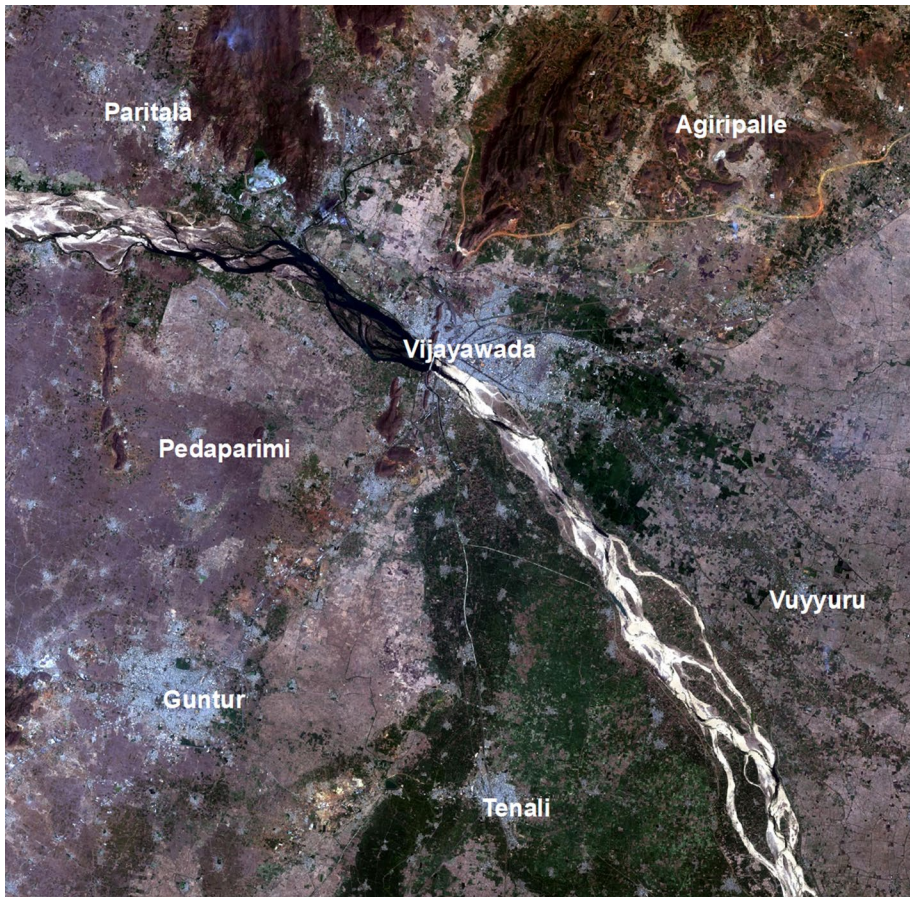


Fig. 1 Study area with imagery sourced from a 2016 Landsat 8 OLI RGB composite image

3.2 Geospatial datasets used

Several open-source geospatial datasets were used for this analysis. Multispectral Landsat 8 OLI imagery with a 30 m resolution was used to develop land use classifications, NDVI (Normalized Difference Vegetation Index), and NDWI (Normalized Difference Water Index). Scene *LC81420492016082LGN0*, obtained from USGS Glovis—which was acquired on March 22nd, 2016—was chosen owing to its lack of cloud cover. To measure elevation and create a flow accumulation map in ArcMap 10.4, ASTER 30 m global digital elevation map (DEM)—developed by NASA and METI—was utilized and downloaded from USGS EarthExplorer. Publicly available soil data obtained from SoilGrids.org (accessed from <ftp://ftp.soilgrids.org/data/>) were more granular—at a 250 m resolution. SoilGrids.org provides soil characteristic predictions based on field measurements, statistics, and machine learning from ISRIC World Soil Information and was utilized for regional analysis of sand percentage, clay percentage, and bulk density at 0.0, 0.15, 0.3, 1.0, and 2.0 m depths.

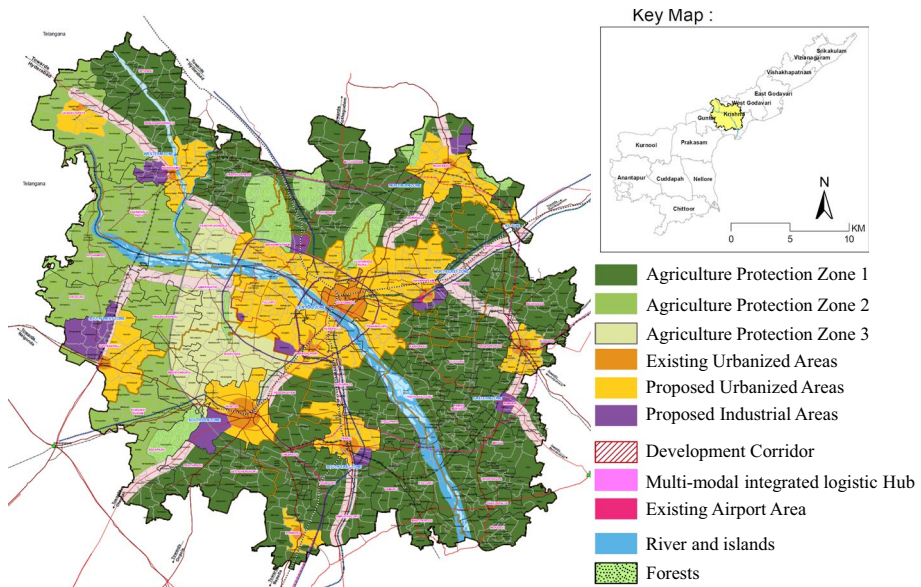


Fig. 2 APCRDA 2050 land use scenario for the immediate Amaravati region. *Note:* for high-resolution image see Supplementary Material (Andhra Pradesh Capital Region Development Authority 2015)

3.3 Methodological framework

The methodology used to generate final guidance maps is illustrated in Fig. 3 (Bardhan 2017). Raw multispectral Landsat 8 data were corrected to top-of-atmosphere reflectance in ENVI 5.4. Band math was then performed to generate NDVI and NDWI for the region. LULC (land use/land cover) classification on the reflectance-corrected image was done in ArcMap 10.4 and verified via an accuracy assessment in ArcMap and Microsoft Excel. The 2050 LULC raster map was created by geo-referencing APCRDA-predicted urban cover for 2050 and superimposing this atop the verified 2016 LULC raster map. This analysis allowed for carbon storage and surface runoff values to be applied to the classified raster by LULC type—which were utilized in creating composite environmental services and flood risk maps, respectively. Soil property maps were also utilized in the production of these two maps—methods here are explained more thoroughly in Sects. 3.11 and 3.12. ASTER elevation data were processed through ArcMap to create a flow accumulation map, which was applied to flood risk and optimal green infrastructure placement maps in addition to the DEM itself.

3.4 Land use classification

Land use classification of geospatial imagery both provides visual representation of urbanization and allows modeling based on assumed properties of a surface cover such as runoff coefficients or carbon storage. Landsat 8 imagery was processed through ENVI 5.4 and ArcMap 10.4 to develop a 2017 land use classification in the Amaravati region. A March 22nd 2016 Landsat 8 image of the Amaravati area was used as the basis of the land use (LULC) classification. In ENVI 5.4, the 7 bands of the original image were corrected to

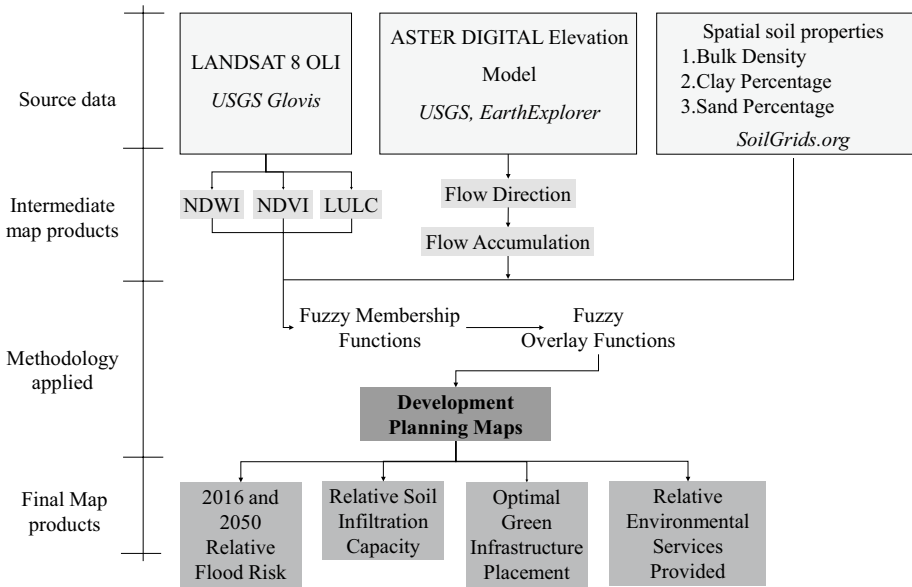


Fig. 3 Methodological flowchart indicating source data, intermediate map products, and final map products

represent top-of-atmosphere reflectance. The band gains and offsets were calibrated using the sine of the sun elevation provided in the Landsat 8 metadata (Exelis 2017). In ArcMap 10.4, training samples were drawn to distinguish between five land types: impervious surface area, forest, bare land, agriculture, and water. The chosen land types were based on Yan et al. (2016). To distinguish between bare land and agricultural land, an NDVI overlay was used in addition to visual inspection of land cover.

3.5 Verification of land use classification with confusion matrix

Verification of the Landsat 8 land use classification was done in ArcMap 10.4 and Microsoft Excel (Albert et al. 2014; Penn 2017). A confusion matrix was generated using reference points of known surface cover, shown in Table 1, with a kappa score of 0.957.

3.6 Land use scenario and assumptions for 2050

To generate a LULC scenario for the year 2050, the urban and industrial expansion forecast by APCRDA was superimposed on the 2017 LULC map generated from the March 2017 Landsat 8 image. The bounds of this expansion were estimated by geo-referencing the APCRDA 2050 Draft Perspective Plan to the Landsat 8 image of the region (APCRDA 2015). Several assumptions made for creating the 2050 LULC scenario are:

1. Urban land coverage in 2050 will match that forecast by APCRDA.
2. Industrial land coverage in 2050 will have similar surface runoff to urban land cover.
3. There is an urban development boundary around Amaravati—no urban expansion will occur outside of the borders defined by APCRDA.
4. There will be a comparable ratio of bare land to agricultural land in 2017 and 2050.

Table 1 Confusion Matrix for LULC Classification Verification

Land type	Water	Bare	Cropland	Forest	ISA	Reference totals	Classified totals	Number correct	Producer accuracy (%)	User accuracy (%)
Water	32	0	0	0	0	34	32	32	94.1	100.0
Bare	0	45	0	0	0	46	45	45	97.8	100.0
Cropland	2	1	48	1	0	48	52	48	100.0	92.3
Forest	0	0	0	34	0	35	34	34	97.1	100.0
ISA	0	0	0	0	63	63	63	63	100.0	100.0

5. The average NDWI values for urban areas in 2016 will equal those in 2050.

3.7 NDVI and NDWI

Normalized Difference Vegetation and Water Indices (NDVI and NDWI) were generated from the reflectance-corrected Landsat 8 OLI bands. The NDVI equation was determined through Tucker (1979) and NDWI through McFeeters (1996). The following equations were carried out in ArcMap 10.4 Raster Calculator:

$$NDVI = \frac{(Near\ Infrared - Red)}{(Near\ Infrared + Red)} = \frac{(Band\ 5 - Band\ 4)}{(Band\ 5 + Band\ 4)}$$

$$NDWI = \frac{(Green - Near\ Infrared)}{(Green + Near\ Infrared)} = \frac{(Band\ 3 - Band\ 5)}{(Band\ 3 + Band\ 5)}$$

3.8 Choice of land use runoff coefficient and carbon storage values

Runoff values were chosen from Dhakal et al. (2012) based on their analysis of LULC types selected by the United States Geological Survey’s National Land Cover Database. The value for ISA was assumed to be that of medium-intensity developed lands, defined as an area covered by 70% impervious surface. Values for soil and vegetative carbon for bare land, cropland, and ISA were determined from Yan et al. (2016), while forest carbon stocks were chosen from the Intergovernmental Panel on Climate Change (2006) Guidelines for National Greenhouse Gas Inventories (Table 2).

3.9 Relative Environmental Services Provided Index (RESPI)

Using index for creating cumulative values or integrated analyses of environmental data in a variety of contexts is well documented (Banzhaf and Boyd 2012; Haines-Young and Potschin 2009; Rodríguez-Loinaz et al. 2014; Van der Biest et al. 2013; Yang et al. 2013). Mostly the tangible and intangible benefits of environment are captured in indicators like ecosystem services index (MEA 2005), Ecosystem Service Bundle Index (EBI) (Van der Biest et al. 2013), index of dependence on ecosystem services (IDES) system (Yang et al. 2013), multiple ecosystem services landscape index (MESLI) (Rodríguez-Loinaz et al. 2014), or Social Values for Ecosystem Services (SolVES) which quantifies values of ecosystems by integrating attitude and preference of people with physical environment (Sherrouse et al. 2011). However, these indices primarily capture the one-time stock of the environmental services available, while it is vital to capture the value of these services in terms of their supporting systems, namely the biophysical potential for the delivery of services.

Table 2 Literature values chosen for runoff coefficients and carbon storage

Land type	Runoff coefficient	Vegetation carbon (kg C/m ²)	Soil carbon (kg C/m ²)	Carbon total (kg C/m ²)
Bare land	0.30	0.04	5.55	5.59
Cropland	0.40	0.64	9.94	10.58
Forest	0.48	13.00	3.64	16.64
ISA	0.65	0.00	5.36	5.36

This is more essential while generating aggregate indices which are intended be used for land use planning. Mostly, the environmental services required for land use planning are external to the market system; hence, safeguarding them for a sustainable development is required (Rodríguez-Loinaz et al. 2014). The “index number problem” (which is generally used for generating the indices) suggests that the aggregated environmental services must be able to facilitate comparisons across time and space using a constant set of value weights. Additionally, capturing the spatial flows of the environmental services is a must for identifying priority areas is essential for optimizing land use and maximizing the extent to which the potential is realized (Bastian et al. 2012; Van der Biest et al. 2013; Verhagen et al. 2017). The existing indices mostly enable powerful metrics that can create policy awareness; however, they are insufficient for land use and policy planning, especially for incorporating the environmental services for climate resilient planning. Here, the Relative Environmental Services Provided Index (RESPI) is devised that can capture the environmental potential and uncertainty to deliver services for climate resilient planning. Relative Environmental Services Provided Index (RESPI) enables in cost-effective and ecologically sound development through composite visualization of carbon storage, greenery, runoff coefficients, and soil flood prevention. To account for the uncertainty in the environmental service potential and to describe the spatial variability, RESPI is devised through a GIS-based fuzzy interface system.

3.10 Fuzzy membership

A fuzzy logic approach was used to combine multiple flood risk factors into a relative flood risk map, a relative soil infiltration map, and the RESPI index (Bardhan 2017). In fuzzy logic, a value between 0 and 1 is assigned to a factor—describing the probability that it belongs to a certain set of data. Mathematical relationships can be used to define the relationship between the factors and their membership to a group. ArcGIS 10.4 can implement fuzzy membership of spatial datasets and overlay these to generate composite probability maps.

As shown in Fig. 4, the linear function is utilized for assumptions of either positive or negative linear relationships between the map layer and membership. The fuzzy large membership function—useful when weighting larger parameter values more heavily—is refined through selection of midpoint and spread values. The fuzzy small model is similar, but provides more weight toward lower parameter values. In this study, the dataset medians were used as midpoints and a spread of 2 was applied for all parameters using these functions unless otherwise noted. The choice of membership functions is based on the premise that environmental services vary significantly across the landscape and are defined as a composite and hierarchical process (Locatelli et al. 2011; Ruíz-López et al. 2012). The impact of the environmental services on the land use also varies linearly with its availability, i.e., higher values (or lower) have higher (or lower) impact.

3.11 Fuzzy overlay methods

All of the composite maps were overlaid utilizing the ArcMap 10.4 gamma function, which is a combination of fuzzy sum and fuzzy product overlays. The fuzzy sum function is a linear combination function that produces results larger than the inputs, while the fuzzy product function simply multiplies the fuzzy membership values of each factor—producing a smaller value in the fuzzy overlay. A fuzzy gamma function with a factor of 0.95 was

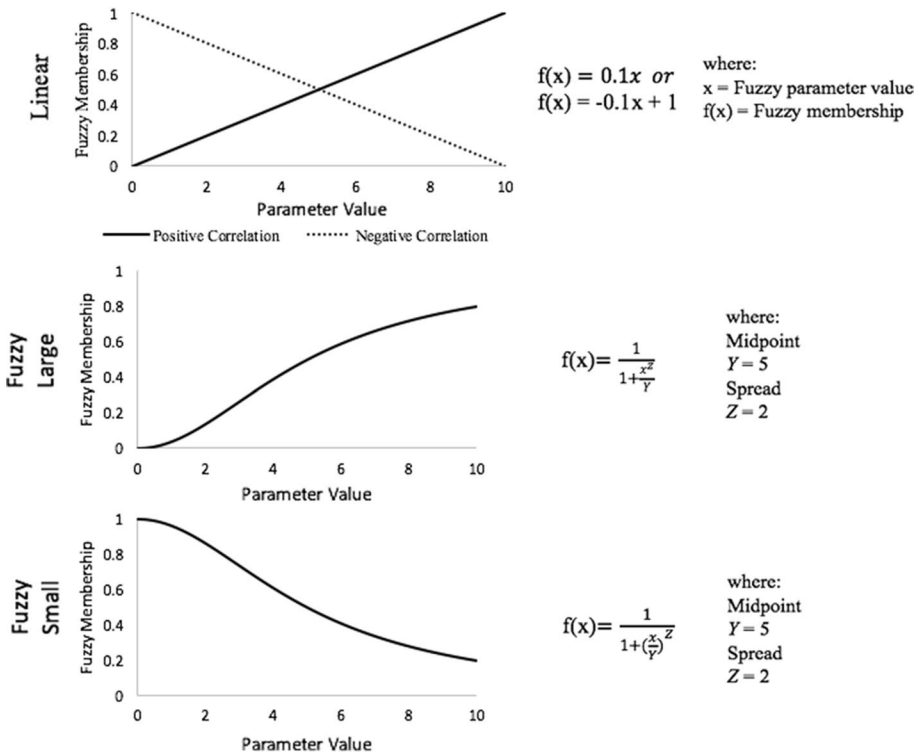


Fig. 4 Graphical representation of the three fuzzy membership functions and the corresponding equations used. *Source:* Environmental Systems Research Institute (2016)

utilized in order to obtain values slightly smaller than the fuzzy sum function alone. The three overlay functions are performed according to the following equations (ESRI 2017a, b):

$$\text{Fuzzy Sum Value} = 1 - ((1 - \text{layer 1}) * (1 - \text{layer 2}) \dots)$$

$$\text{Fuzzy Product Value} = \text{layer 1} * \text{layer 2} \dots$$

$$\text{Fuzzy Gamma Value} = \text{Fuzzy Sum}^\gamma * \text{Fuzzy Product}^{1-\gamma}$$

3.12 Relative soil infiltration fuzzy membership

A geospatial index was created using publicly available data to estimate the relative infiltration capacity of soil within the immediate Amaravati region. Clay percentage, sand percentage, and bulk density have all been correlated to hydraulic conductivity (Assouline 2006; Benson et al. 1994) and infiltration (Kalantari et al. 2014). For instance, areas with larger fractions of sands have greater infiltration rates than clays due to larger pore size and tightly packed soils with higher bulk densities limit infiltration. Global geospatial data for these properties provided a proxy for hydraulic conductivity and soil infiltration capacity. A map of relative soil infiltration rates can inform development patterns and engineered storm water projects to reduce flood risk and increase

project value. Potentially urbanized areas with greater infiltration capacity could be prioritized for protection, or for projects such as permeable pavement or bio-swales.

Several soil depths were incorporated to more accurately estimate infiltration capacity than using surface infiltration alone. From SoilGrids.org, 250 m resolution maps of each soil property at 0.0, 0.15, 0.3, 1.0, and 2.0 m depths were obtained. As shown in Table 3, each property was weighted according to the fuzzy large function with a spread of five and midpoint of one to in order to more heavily weight surface soils—which are more relevant to infiltration. For each of the three soil properties, an overlay was created in ArcMap according to these weights.

The final step for creating the relative soil infiltration map was to perform fuzzy membership and overlay for the three soil properties—as described in Table 4. This map was later utilized to create the RESPI map and optimal green infrastructure map.

3.13 Relative flood risk map fuzzy membership

Soil properties were considered alongside other flood risk factors to develop a relative flood risk map for the immediate Amaravati region. The overlay of these fuzzy memberships was performed for 2016 and 2050 scenarios, the difference in the scenarios being the changes in surface runoff due to LULC changes and NDWI. In order to quantify the effect of increased ISA on moisture content for the 2050 urbanization scenario, the average NDWI value of ISA classified areas in the 2016 LANDSAT 8 image, $NDWI = -0.266$, was applied to the expanded urban cover for the 2050 scenario (Tables 5, 6, 7, 8).

3.14 Relative Environmental Services Provided Index (RESPI) fuzzy membership

In order to better inform intelligent urban development, it is imperative to understand the spatial variation of environmental services such as carbon storage, infiltration capacity, and primary production and greenery. Similarly, it is possible to maximize environmental services in a future development scenario such as in Amaravati. Fuzzy membership was used to correlate carbon storage, surface runoff, relative soil infiltration, and NDVI to provide an approximation of environmental services provided by land cover in the region. Here, we devised a Relative Environmental Services Provided Index (RESPI) that acts as an indicator of the environmental service status in the region. Areas classified as impervious surfaces were given null values for RESPI.

Table 3 Soil property weighting based on depth of dataset

Soil property depth (m)	Overlay weight
0	0.970
0.15	0.956
0.3	0.934
1.0	0.500
2.0	0

Table 4 Relative soil infiltration fuzzy membership summary

Soil property	Fuzzy membership type	Rationale	Data source
Bulk density	Fuzzy small	The weight of soil per volume. Smaller bulk densities are more heavily weighted toward infiltration	SoilGrids.org (accessed on July 22, 2018) Dec et al. (2008)
Sand percentage	Linear	Percentage of sand by volume (50–2000 μm). Positively correlated with infiltration	SoilGrids.org (accessed on July 22, 2018) Dec et al. (2008)
Clay percentage	Fuzzy small	Percentage of clay by volume (0–2 μm). Negatively correlated with infiltration	SoilGrids.org (accessed on July 22, 2018) Dec et al. (2008)

Table 5 Relative overall flood risk fuzzy membership summary

Flood risk factor	Fuzzy membership type	Rationale	Data source
Elevation	Fuzzy small	Lower elevations were more heavily weighted toward flood risk	Landsat 8 OLI
Flow accumulation map	Fuzzy large	Generated in ArcMap 10.4 from DEM by using Flow Direction and Flow Accumulation tools. High flow accumulation was more heavily weighted toward flood risk	Landsat 8 OLI
Surface runoff	Linear	High surface runoff is correlated with pooling and lack of infiltration Positively correlated to flood risk	Section 3.4, Dhakal et al. (2012)
Soil infiltration capacity	Linear	An overlay of soil properties identifying regions of relatively high infiltration capacity as defined in Sect. 3.11. Negatively correlated to flood risk	Section 3.11, SoilGrids.org (accessed on July 22, 2018)
NDWI	Linear	Normalized difference water index, a measure of relative moisture content. Higher moisture content or existing water bodies indicate higher flood potential	Section 3.7, Bardhan (2017)

Table 6 Relative environmental services provided fuzzy membership summary

RESPI factor	Fuzzy membership type	Rationale	Data source
Carbon storage	Linear	Kg of Carbon sequestered in soil and above ground biomass—positively correlated	Section 3.8, Yan et al. (2016), IPCC (2006)
Surface runoff	Linear	Rational method surface runoff coefficients were assigned based on assigned LULC classification—negatively correlated	Section 3.4, Dhakal et al. (2012)
Soil infiltration capacity	Linear	Relative infiltration capacity of soil, see Sect. 2.9. Positively correlated to RESPI	Section 3.11, SoilGrids.org (accessed on July 22, 2018)
NDVI	Linear	Reflectance index used to discern areas of vegetated cover and primary production. Positively correlated to RESPI	Section 3.7

Table 7 Optimal green infrastructure placement fuzzy membership summary

Placement factor	Fuzzy membership type	Rationale	Data source
Elevation	Fuzzy small	Water is more likely to pool at lower elevations	ASTER DEM
Flow accumulation map	Fuzzy large	Green infrastructure is most valuable in areas of high flow accumulation	Section 3.3
Soil infiltration capacity	Linear	Relative infiltration capacity of soil—positively correlated to green infrastructure feasibility	Section 3.11

Table 8 LULC coverage scenarios

LULC Type	2016 coverage fraction	2050 coverage fraction
ISA	0.071	0.336
Forest	0.056	0.048
Cropland	0.516	0.362
Bare soil	0.351	0.249
Water bodies	0.006	0.005

3.15 Optimal green infrastructure placement fuzzy membership

Placement of green infrastructure such as permeable pavement, bio-swales, and infiltration basins are more effective in areas with greater soil infiltration capacity. These systems should be prioritized for regions at low elevation, where they are most needed for flood prevention services. To inform economical placement of these systems in Amaravati, a composite map was created through fuzzy overlay of elevation and soil infiltration capacity.

3.16 Results and discussion

Figure 5a shows the result of land classification analysis of the March 22nd, 2016, Landsat 8 OLI image. The study area is primarily covered by agricultural land and bare soil, with forested areas concentrated in the northern region of the study area and heavy ISA focused around both Vijayawada and Guntur. Figure 5b illustrates the 2050 scenario created by geo-referencing APCRDA-predicted urban cover. The NDVI (Fig. 5c) and NDWI (Fig. 5d) are also shown. High NDVI values in the western section of the study area correlate with the land designated as cropland by the land classification. The study showed relatively low NDWI results, even for the areas on the River Krishna with open water—the expected NDWI for a perennial river or stream is 0.5 (Bardhan 2017). These low NDWI values for River Krishna could be correlated to high concentrations of sediment or other pollutants in the water.

Table 9 shows changes in land cover fraction in the classified 2016 Landsat image and the 2050 LULC scenario. Expanded urban cover in 2050 was largely accounted for by reductions in bare soil and cropland. Based on the land cover classifications, total estimated carbon sequestration in the region decreased by 3.4 Megatons from 2016 to 2050, driven by a 374% increase in ISA. Similarly, the average rational method runoff coefficient of regional LULC increased from 0.387 to 0.461 over this time period.

Figure 6a, b shows the DEM and relative soil infiltration capacity, respectively, of the Amaravati region as defined by a fuzzy overlay of surface sand percentage, clay percentage, and bulk density. The area surrounding present-day Vijayawada has highly favorable soil for infiltration, while the planned central zone of Amaravati sits atop soil with relatively higher clay content and higher bulk density, limiting infiltration ability. A SoilGrids map of soil types (not shown) illustrated that the region is primarily occupied by vertisol soils which are high in clay below 50 cm and can also form surface cracks during dry seasons if not irrigated (FAO 2017). There is generally higher infiltration capacity along the River Krishna due to larger sand fractions, though this is less pronounced in the planned central zone of the capital. As a result, in the capital region storm water retention technologies such as storage ponds could be a more effective option than storm water infiltration.

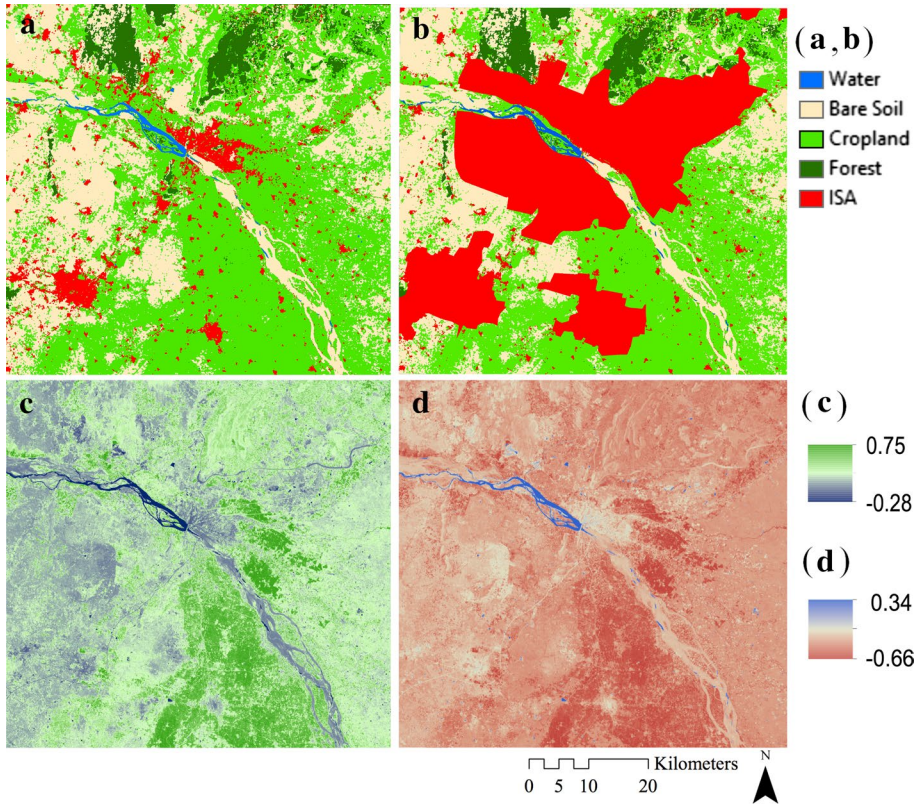


Fig. 5 2016 (a) and 2050 (b), LULC classifications, c NDVI, d NDWI—all derived from Landsat 8 OLI imagery

Table 9 Carbon storage scenarios

LULC type	2016 carbon (megatons C)	2050 carbon (megatons C)
ISA	1.47	6.82
Forest	3.63	3.02
Cropland	21.2	15.2
Bare soil	7.58	5.43
Water bodies	N/A	N/A
Total	33.9	30.5

Figure 7a, b shows the relative flood risk maps for 2016 and 2050, respectively, as predicted by application fuzzy logic to flood risk factors. Expansion of high flood risk areas in the 2050 scenario is correlated with the higher surface runoff of urbanized areas. Areas of lower flood risk within urbanized regions are caused by favorable soil infiltration properties and higher elevations—though this not the case in the planned central capital region west of Vijayawada where predicted flood risk is high in 2050. In the 2016 scenario, areas

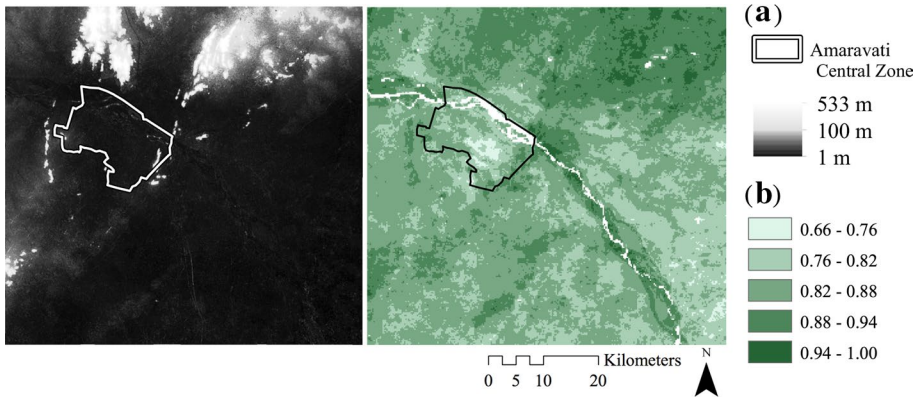


Fig. 6 a Digital elevation map, b relative soil infiltration capacity

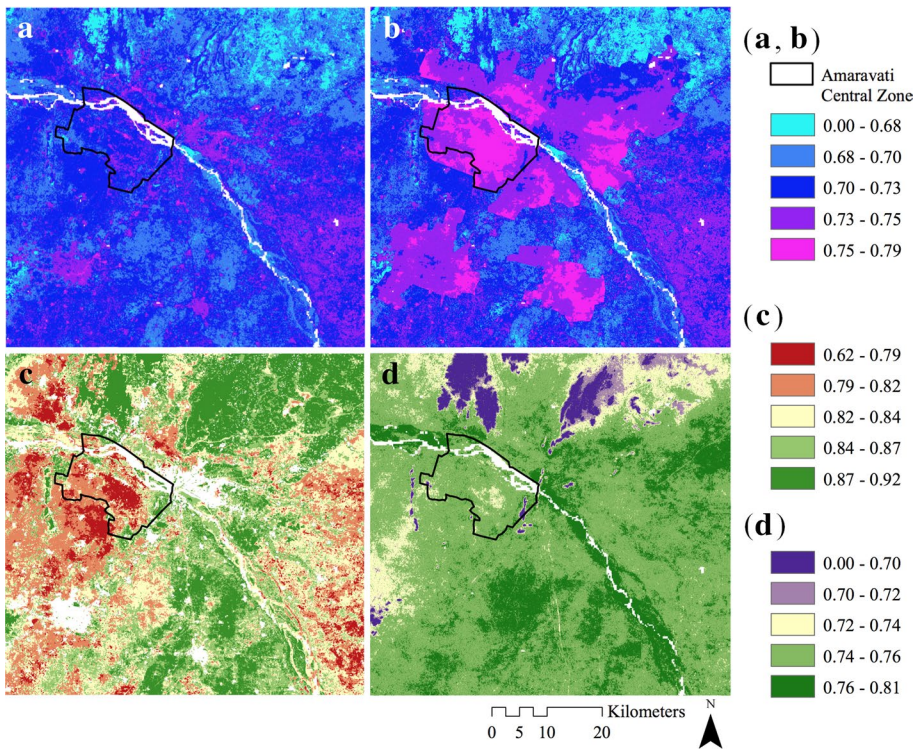


Fig. 7 Fuzzy overlay results: a 2016 relative flood risk, b 2050 relative flood risk, c Relative Environmental Services Provided Index (RESPI), d optimal green infrastructure placement

of high relative risk are pronounced near Vijayawada, Guntur, and Tenali. In Vijayawada, higher flood risks are found on the outskirts of the current urban sprawl—where soils have lower infiltration capacities than the city center, as shown in Fig. 6b. This is also seen in

the 2050 scenario, where soils of higher sand content correlate to lowered flood risk within the expanded urban areas.

Figure 7c denotes spatial differences in regional environmental services, including soil infiltration, lower runoff, carbon storage, and NDVI. Areas currently occupied by urban cover are not included in this index and appear as white. The low values west of present-day Vijayawada stem from particularly low infiltration capacity and lower carbon storage and NDVI due to bare land cover. Higher rated forested areas in the north result from higher carbon storage. The overlay of elevation, flow accumulation, and soil infiltration properties in Fig. 7d identifies areas where there is both high flood risk and soil properties are conducive to the effectiveness of infiltration basins, bio-swales, and permeable pavement. Areas adjacent to River Krishna have higher ratings for green infrastructure as a result of high sand fractions.

These maps are intended to illustrate high-value land providing environmental services that will contribute to the sustainability of the planned smart city Amaravati and the surrounding region. While the RESPI and Green Infrastructure maps are intended to serve as guidance for development in the Amaravati region, any specific actions must be accompanied by significant further investigation. Local-scale green infrastructure projects, for example, would require additional ground verification of soil properties as well as watershed delineation. Likewise, the Relative Flood Risk maps are intended to bring attention to areas deemed particularly vulnerable to flooding in the present-day and the 2050 scenario—including the central zone of the planned capital city.

4 Conclusions and future work

As rapid development is expected in the immediate Amaravati region, there is great opportunity to combine the power of open-source data and ground observation for useful geospatial and hydrological analyses. Growth in ISA, in conjunction with expected increased in storm intensity as a result of climate change, necessitates that city planners consider spatial differences in soil infiltration ability and overall flood risk to minimize future flood damages and maximize efficiency of green infrastructure with the limited municipal funds available. In this study, Landsat 8 OLI imagery, spatial distinctions in soil properties, and elevation maps were utilized to create regional maps with the intention of supporting decision-makers and guiding more localized inquiries into flood risk and storm water runoff reduction initiatives.

Creation of 2016 and 2050 LULC maps from Landsat 8 OLI imagery and APCRDA scenarios revealed a reduction in environmental carbon sequestration, from 33.9 to 30.5 megatons within the study area. Additionally, the average surface runoff coefficient increased from 0.387 to 0.461—driven by a 374% increase in ISA. The soil infiltration capacity map revealed relatively low infiltration capacity at the planned central zone of Amaravati and its immediate outskirts, suggesting that storm water detention techniques could be particularly applicable. Conditions were more favorable for infiltration-centered designs across River Krishna at Vijayawada. The optimal green infrastructure placement map—correlating areas of low elevation with areas of high infiltration capacity—points to locations with sandy soils adjacent to River Krishna which could be prioritized for protection from complete surface paving to facilitate storm water drainage. Additionally, in the northwest region of Tenali, a combination of low elevations and favorable soil properties suggests favorable conditions.

The RESPI map—illustrative of environmental services—shows high values in forested regions due to their carbon sequestration capacity and in cropland due to an increased NDVI. Meanwhile, the areas around the Amaravati central zone are markedly low in this index. This insinuates that there is less environmental consequence in terms of net carbon storage and infiltration ability loss. However, increased ISA in such areas could cause relatively higher flood risks when compared to Vijayawada due to the lower initial infiltration capacity of the surrounding soils.

The maps produced in this study can inform regional development planning for the Amaravati region, but future work remains to generate hydrological models and quantitative flood risk maps that assess the risk of increases in impervious surface area. Integration of spatial soil properties into these maps will be a vital component to informing more localized placement of engineered storm water systems and determining whether infiltration technologies such as permeable pavement or storm water detention technologies such as underground storage tanks are more appropriate. Integration of socioeconomic data into such models could aid in the quantification of the long-term benefits of green infrastructure and ensure that the benefits of sustainable development are being distributed equitably across income groups and regions.

The authors invite governmental review and input for consideration as a follow-up to this article. Continued collaboration between government planning agencies, academic institutions, NGOs, and the private sector will be necessary to fulfill the ideal “no-flood” future for Amaravati. Future work could include obtaining granular data sources on precipitation, soil cores, solar radiation, and wind speed—in order to improve the depth of the fuzzy logic models. Combing fuzzy flood risk maps with 100- and 500-year floodplains could provide a thorough model relevant for both flood risk and possible preventative alternatives.

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References

- Albert L, Rottensteiner F, Heipke C (2014) Land use classification using conditional random fields for the verification of geospatial databases. *ISPRS Ann Photogramm Remote Sens Spat Inf Sci II-4*:1–7. <https://doi.org/10.5194/isprsannals-II-4-1-2014>
- Amaravati Development Corporation Ltd (ADC), Andhra Pradesh Capital Region Development Authority (2017) Smart city Amaravati integrated infrastructure master plan. Retrieved July 22, 2017 from https://crda.ap.gov.in/apcrda/communi/media/APCRDADOCS/Amaravati%20Concept%20Handbook_Modified.pdf
- Andhra Pradesh Capital Region Development Authority (2015) Draft perspective plan - 2050 for APCRDA region. Retrieved December 29, 2017, from https://crda.ap.gov.in/APCRDA/Downloads/MasterPlans/Draft_Perspective_Plan-2050_for_APCRDA.pdf
- Assouline S (2006) Modeling the relationship between soil bulk density and the hydraulic conductivity function. *Vadose Zone J* 5:554–563. <https://doi.org/10.2136/vzj2005.0083>
- Banzhaf HS, Boyd J (2012) The architecture and measurement of an ecosystem services index. *Sustainability* 4(4):430–461. <https://doi.org/10.3390/su4040430>
- Bardhan R (2017) Integrating rapid assessment of flood proneness into urban planning under data constraints: a fuzzy logic and bricolage approach. *Area Dev Policy*. <https://doi.org/10.1080/23792949.2017.1338523>

- Bardhan R, Kurisu K, Hanaki K (2011) Linking urban form & quality of life in Kolkata, India. In: 47th ISO-CARP congress liveable cities - Urbanizing world: meeting the challenge (pp. 1–12). Wuhan, China: ISOCARP. Retrieved December 29, 2017, from http://www.isocarp.net/data/case_studies/1923.pdf
- Bardhan R, Kurisu K, Hanaki K (2015) Does compact urban forms relate to good quality of life in high density cities of India? Case of Kolkata. *Cities* 48:55–65. <https://doi.org/10.1016/j.cities.2015.06.005>
- Bardhan R, Debnath R, Bandopadhyay S (2016) A conceptual model for identifying the risk susceptibility of urban green spaces using geo-spatial techniques. *Model Earth Syst Environ* 2(3):144. <https://doi.org/10.1007/s40808-016-0202-y>
- Bastian O, Haase D, Grunewald K (2012) Ecosystem properties, potentials and services—the EPPS conceptual framework and an urban application example. *Ecol Ind* 21:7–16. <https://doi.org/10.1016/j.ecoli.2011.03.014>
- Benson CH, Zhai H, Wang X (1994) Estimating hydraulic conductivity of compacted clay liners. *J Geotech Eng (US)* 120:2. [https://doi.org/10.1061/\(asce\)0733-9410\(1994\)120:2\(366\)](https://doi.org/10.1061/(asce)0733-9410(1994)120:2(366))
- Chandramouli C (2011) Rural urban distribution of population. Indian Ministry of Home Affairs. Retrieved December 29, 2017, from http://censusindia.gov.in/2011-prov-results/paper2/data_files/india/Rural_Urban_2011.pdf
- Dec D, Dörner J, Becker-fazekas O, Horn R (2008) Effect of bulk density on hydraulic properties. *J Soil Sci Plant Nutr* 8(1):1–13
- Dhakal N et al (2012) Estimation of volumetric runoff coefficients for Texas watersheds using land-use and rainfall-runoff data. *J Irrig Drain Eng* 138:43–54. [https://doi.org/10.1061/\(ASCE\)IR.1943-4774.0000368](https://doi.org/10.1061/(ASCE)IR.1943-4774.0000368)
- Environmental Systems Research Institute (2016) How fuzzy membership works. Retrieved October 1, 2017, from <http://desktop.arcgis.com/en/arcmap/10.3/tools/spatial-analyst-toolbox/how-fuzzy-membership-works.htm>
- ESRI (2017a) How fuzzy overlay works. Environmental Systems Research Institute. Retrieved January 22, 2018 from <http://pro.arcgis.com/en/pro-app/arcpy/spatial-analyst/an-overview-of-fuzzy-classes.htm>
- ESRI (2017b) An overview of fuzzy classes. Environmental Systems Research Institute. Retrieved January 22, 2018 from <http://pro.arcgis.com/en/pro-app/arcpy/spatial-analyst/an-overview-of-fuzzy-classes.htm>
- Exelis Visual Information Solutions, Inc. (2017) Radiometric calibration. Harris geospatial solutions. Retrieved January 22, 2018 from <https://www.harrisgeospatial.com/docs/RadiometricCalibration.html>
- Fisher B, Turner RK, Morling P (2009) Defining and classifying ecosystem services for decision making. *Ecol Econ* 68(3):643–653. <https://doi.org/10.1016/j.ecolecon.2008.09.014>
- Food and Agriculture Organization of the United Nations (2017) Key to the FAO soil units. Retrieved July 22, 2017 from <http://www.fao.org/soils-portal/soil-survey/soil-classification/fao-legend/key-to-the-fao-soil-units/en/>
- Haines-Young RH, Potschin MB (2009) The links between biodiversity, ecosystem services and human well-being. In: Raffaelli D, Frid C (eds) *Ecosystem ecology: a new synthesis* (BES ecological reviews series). CUP, Cambridge, p 31. <https://doi.org/10.1017/CBO9780511750458>
- India Ministry of Urban Development (2011) Report on Indian urban infrastructure and services. Indian Council for Research on International Economic Relations. Retrieved July 22, 2017 from <http://icrie.org/pdf/FinalReport-hpec.pdf>
- Jana A, Bardhan R, Sarkar S, Kumar V (2016) Framework to assess and locate affordable and accessible housing for developing nations: empirical evidences from Mumbai. *Habitat Int* 57:88–99. <https://doi.org/10.1016/j.habitatint.2016.07.005>
- Kalantari Z, Nickman A, Lyon SW, Olofsson B, Folkesson L (2014) A method for mapping flood hazard along roads. *J Environ Manag* 133:69–77. <https://doi.org/10.1016/j.jenvman.2013.11.032>
- Kishtawal CM, Niyogi D, Tewari M, Pielke RA, Shepherd JM (2010) Urbanization signature in the observed heavy rainfall climatology over India. *Int J Climatol* 30(13):1908–1916. <https://doi.org/10.1002/joc.2044>
- Locatelli B, Imbach P, Vignola R, Metzger MJ, Hidalgo EJL (2011) Ecosystem services and hydroelectricity in Central America: modelling service flows with fuzzy logic and expert knowledge. *Reg Environ Change* 11(2):393–404. <https://doi.org/10.1007/s10113-010-0149-x>
- McFeeters SK (1996) The use of the normalized difference water index (NDWI) in the delineation of open water features. *Int J Remote Sens* 17(7):1425–1432. <https://doi.org/10.1080/01431169608948714>
- Millennium Ecosystem Assessment (MEA) (2005) *Ecosystems and human well-being: synthesis*. Island Press, Washington
- Nagendra H, Sudhira HS, Katti M, Schwenius M (2013) Sub-regional assessment of India: effects of urbanization on land use, biodiversity and ecosystem services. In: Elmqvist T, Fragkias M, Goodness

- J, Güneralp B, Marcotullio PJ, McDonald RI, Parnell S, Schewenius M, Sendstad M, Seto KC, Wilkinson C (eds) Urbanization, biodiversity and ecosystem services: challenges and opportunities: a global assessment, pp 65–74. <https://doi.org/10.1007/978-94-007-7088-1>
- National Institution for Transforming India (2016a) Report on sustainable development goal 11. Government of India. Retrieved December 22, 2017 from http://niti.gov.in/writereaddata/files/Report_SDG-11.pdf
- National Institution for Transforming India (2016b) Sustainable development goals, targets, CSS, interventions, nodal and other ministries. Government of India. Retrieved December 22, 2017 from http://niti.gov.in/writereaddata/files/SDGsV20-Mapping080616-DG_0.pdf
- National Remote Sensing Centre (NRSC), Indian Space Research Organization (2014) Andhra Pradesh disaster management department. Retrieved July 22, 2017 from https://nrsc.gov.in/uim_2014_proceeding/papers_ppts/UIM2014_US5_EVinodKumar.pdf
- Penn State College of Earth and Mineral Sciences (2017) Classification accuracy assessment. Department of Geography. <https://www.e-education.psu.edu/geog883/node/524>. Accessed 22 July 2017
- Pielke RA, Adegoke J, Beltrán-Przekurat A, Hiemstra CA, Lin J, Nair US, Nobis TE (2007) An overview of regional land-use and land-cover impacts on rainfall. *Tellus Ser B Chem Phys Meteorol* 59(3):587–601. <https://doi.org/10.1111/j.1600-0889.2007.00251.x>
- Rodríguez-Loinaz G, Alday JG, Onaindia M (2014) Multiple ecosystem services landscape index: a tool for multifunctional landscapes conservation. *J Environ Manag* 147:152–163. <https://doi.org/10.1016/j.jenvman.2014.09.001>
- Ruíz-López DM, Aragón-Noriega AE, Luna-Gonzalez A, Gonzalez-Ocampo HA (2012) Applying fuzzy logic to assess human perception in relation to conservation plan efficiency measures within a biosphere reserve. *Ambio* 41(5):467–478. <https://doi.org/10.1007/s13280-012-0252-y>
- Sherrouse BC, Clement JM, Semmens DJ (2011) A GIS application for assessing, mapping, and quantifying the social values of ecosystem services. *Appl Geogr* 31(2):748–760. <https://doi.org/10.1016/j.apgeog.2010.08.002>
- Task Force on National Greenhouse Gas Inventories (2006) IPCC guidelines for national greenhouse gas inventories—volume 4: agriculture, forestry, and other land use. Intergovernmental panel on climate change. Retrieved July 22, 2017 from http://www.ipcc-nggip.iges.or.jp/public/2006gl/pdf/4_Volume4/V4_04_Ch4_Forest_Land.pdf
- Tucker Compton J (1979) Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sens Environ* 8(2):127–150. [https://doi.org/10.1016/0034-4257\(79\)90013-0](https://doi.org/10.1016/0034-4257(79)90013-0)
- United Nations Framework Convention on Climate Change (2015) India's intended nationally determined contribution. United Nations. Retrieved July 01, 2017 from <http://www4.unfccc.int/submissions/INDC/Submission%20Pages/submissions.aspx>
- Van der Biest K, D'Hondt R, Jacobs S, Landuyt D, Staes J, Goethals P, Meire P (2013) EBI—an index for delivery of ecosystem service bundles ecological indicators. *Ecosyst Serv Glob Issues Local Pract* 37:263–272. <https://doi.org/10.1016/B978-0-12-419964-4.00020-2>
- Verhagen W, Kukkala AS, Moilanen A, van Teeffelen AJA, Verburg PH (2017) Use of demand for and spatial flow of ecosystem services to identify priority areas. *Conserv Biol* 31(4):860–871. <https://doi.org/10.1111/cobi.12872>
- Wang P, Huang C, Brown de Colstoun EC (2017) Mapping 2000–2010 impervious surface change in india using global land survey landsat data. *Remote Sens* 9(4):366
- World Bank (2013) India: climate change impacts. The World Bank Group. Retrieved July 02, 2017 from <http://www.worldbank.org/en/news/feature/2013/06/19/india-climate-change-impacts>
- Yan Y, Zhang C, Hu Y, Kuang W (2016) Urban land-cover change and its impact on the ecosystem carbon storage in a dryland city. *Remote Sens* 8(1):1–18. <https://doi.org/10.3390/rs8010006>
- Yang W, Dietz T, Liu W, Luo J, Liu J (2013) Going beyond the millennium ecosystem assessment: an index system of human dependence on ecosystem services. *PLoS ONE*. <https://doi.org/10.1371/journal.pone.0064581>
- Zope PE, Eldho TI, Jothiprakash V (2017) Hydrological impacts of land-use cover change and detention basins on urban flood hazard: a case study of Poisar River basin, Mumbai, India. *Nat Hazards* 87:1267–1283. <https://doi.org/10.1007/s11069-017-2816-4>