

A conceptual model for identifying the risk susceptibility of urban green spaces using geo-spatial techniques

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Abstract Urban green spaces are often regarded as the harbinger of sustainability in the rapidly urbanizing world. This study forwards a conceptual framework towards urban green space (UGS) management by the quantification of risk susceptibility of the UGS at a neighborhood level by using remote sensing data and geo-spatial techniques. Objective measure of the UGS was performed using weighted evaluation of NDVI data at a 20 m × 20 m grid over the city of Kolkata. The normalized green index (NGI) was developed to quantify the implication of the built-up spaces in UGS risk susceptibility in the urban fabric. Both the satellite image data and the NGI values were spatially auto-correlated using bivariate Moran's I to derive the intricate relationship between built-up area and green spaces using LISA. It was observed that the low green-spaces were greatly influenced by the high built-up area around it. This inference was extended on the Kolkata's grid, the results revealed that the older part of the city had the most risk susceptible zones, whereas the area surrounded by wetlands were the most stable region bearing high resilience to urbanization. Hence, by determining the most risky zones for UGS degradation, planners and policy makers can efficiently allocate resources towards the sustainable development of the city by conserving and promoting UGS.

Keywords Urban green spaces · Geo-spatial · Concept-model · Environment · Spatial-autocorrelation

Introduction

Sustainable development goals (SDG) no. 15, aims at protecting, restoring and promoting sustainable use of terrestrial ecosystems, sustainably manage forest and combat desertification by conserving land degradation and preventing biodiversity loss by 2030 (United Nations 2014). Rapid urbanization and population explosion is the biggest force that is irreversibly transforming terrestrial ecosystems. 11 out of 19 megacities of the world, with more than 10 million inhabitants are in Asia, with India and China alone accommodates more than 1 billion population (Zhao et al. 2006). Here, more than 50 % of the population lives in less than 3 % of the urbanized terrestrial surface, creating tremendous pressure on the land, triggering ecological consequences (Singh et al. 2010). Rapid urbanization in India is changing the dynamics between ecology, economy and the society. In the last 50 years, the urban population in India has grown fivefolds, where 60 % of this growth is attributable to natural growth, and the remaining 40 % is due to migration and spatial expansion (Sivaramakrishnan et al. 2005; Taubenböck et al. 2009). The urban population in India is likely to grow to 500 million in the next 50 years, and will continue to have substantial impact on the ecology, economy and society at local, regional, and global scales (Singh et al. 2010). Hence, redesigning and optimizing urban systems to mitigate the impact of rapid urbanization and population expansion, while being carbon neutral, is an urgent necessity to combat climate change, and is a serious public policy and adaptation management challenge for India (Revi 2008).

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In this purview, one of the effective policy instrument is the protection of green-areas within urban social-ecological systems to amend several problems of city-living. Green areas or the 'Urban Green Spaces (UGS)' in the city comprises all urban parks, forests and related vegetation that add value to the urbanites (Gupta et al. 2012). The benefits of UGS are wide ranging that include enhancing of public health, social solidity, climate change mitigation, pollution reduction, biodiversity conservation and uplift the quality of ecosystem services (Singh et al. 2010). Apart from maintaining the quality and sustainability, UGS functions as a visual screen and act as noise barriers and avoid too much spatial uniformity (Gupta et al. 2012). Hence in one word green spaces contribute in reducing urban vulnerabilities.

Global UGS estimation suggests that developed countries have more green spaces compared to the cities in developing countries, which often fall below the minimum standards of 9 m² green open space per city dweller by the World Health Organization (WHO) (Singh et al. 2010). The UGS coverage in India are not well-studied, some studies on Bangalore (Nagendra and Gopal 2011; Sudha and Ravindranath 2000), Delhi (FSI 2009) and Chandigarh (Chaudhry and Tewari 2010), focus more on the subjective methods of perceived, self-reported hedonism about green spaces involve the method of survey question audit by trained raters who apply specific criteria (e.g., presence/absence of various features) to assess natural environments. Such subjective measures are time consuming and expensive (Gupta et al. 2012). With the advent of remote sensing (RS) and geographical information system (GIS), objective measures of UGS have become more communicative, by virtue of its receptivity, synoptic view and larger area coverage. Forster (1983) showed the applicability of Landsat imagery for producing quality index for urban areas which included rating of green spaces (Gupta et al. 2012; Sivaramakrishnan et al. 2005; Sudha and Ravindranath 2000). Liu and Liu (2008) estimated green spaces using the ecological niche modeling technique, but concluded that it should not be used for UGS construction, as it does not address spaces and human barrier conflicts. Image processing allows extraction of features of interest, based on reflectance characteristics, from satellite data in the form of indices through different algorithms and mathematical indices. The Normalized Difference Vegetation Index (NDVI) is one such index that is used to highlight vegetation areas on a remote sensing data and is widely applied for studying global environmental and climate change (Gao 1996). It is calculated as a ratio difference between measured canopy reflectance in the red and near infrared bands respectively (Bhandari et al. 2012). The use of GIS has proved useful in identifying vegetation cover, preparing urban green data inventory and mapping

potential value of a green areas using various attribute and location-based queries and, data integration techniques. Assessing multi-attribute values like risk or vulnerability of such urban assets can also be performed in GIS using advanced spatial algorithms, like multi-criteria mapping, spatial overlay, spatial auto-correlation and spatial regression. Such techniques enable in identifying spatial hot and cold spots of risks and vulnerability.

In city planning, UGS are considered as a key element for reducing urban vulnerability from external stresses of urbanization, hence are often treated as homogeneous goods, whose loss can be quantified as a uniform value reduction in a continuum scale (Lee et al. 2015; McConnells and Walls 2005). However, in reality it is more complex, they are actually heterogeneous goods having hierarchy of distinct values based on the functionality and services they provide. Thus create varied resistance towards urban vulnerability reduction.

The efficiency of UGS are dependent on their own risk liability. Urban green assets has an inherent resiliency, which is a function of the intrinsic risk susceptibility of the green space, based on its regeneration and rejuvenation capability and contextual association to built-spaces. Therefore, to internalize the beneficiary role of UGS, not all green spaces need to be statutorily preserved at the same time. This innate risk of the UGS can be utilized to derive a hierarchical UGS risk function and only those greens that are at immediate threat to extinction or will collapse can be preserved. Currently there exists no standard methodology to identify the risk susceptibility of the UGS. Studies that deal with the quality of green spaces mostly focus on characterizing them based on multiple environmental attributes and rarely address the issue of the intrinsic resilience. (Gupta et al. 2012; Sati et al. 2016). Remote sensing and GIS techniques can be aptly used for this function.

In this study we forward a conceptual framework for identifying the risk susceptibility of UGS as an effect of urbanization. Here, the risk susceptibility of UGS is defined as a function of its greenness or the vegetation health and its exposure to stress from urbanization. We use satellite imagery to capture the status of UGS in a rapidly urbanizing area, and generate a green space risk susceptibility map using Anselin's (1995) spatial dependence model of bivariate-Local Index of Spatial Association (LISA).

Conceptual framework

Urban green spaces are an intrinsic part of a sustainable built environment. The importance of green spaces in the neighborhood transcends environmental, social and economic benefits. However, there are complex risks

associated with the development and conservation of UGS. In this study, we forward a methodology that would not only help planners or policy makers to decide how much emphasis should be given to a particular spatial range of UGS, but also optimize resource allocation, in the preservation, protection and conservation of it. This work picks from the concluding remarks of Gupta et al. (2012) where they derived a tool/technique to objectively measure the quality of green spaces in an urban neighborhood using RS and GIS technology. They concluded by converging their study towards the importance of such RS enabled tool at the household level for urban-environment sustainability. Here, we pick this end and put forward a conceptual framework for studying the risk susceptibility decision making of UGS from built-space interaction.

The risk of a system can be defined as the combined function of exposure to stresses (which leads to vulnerability) and inherent resiliency (i.e., the ability to cope with the stress). Here the risk susceptibility of UGS is defined as the product of exposure to urbanization stresses (E_u) and

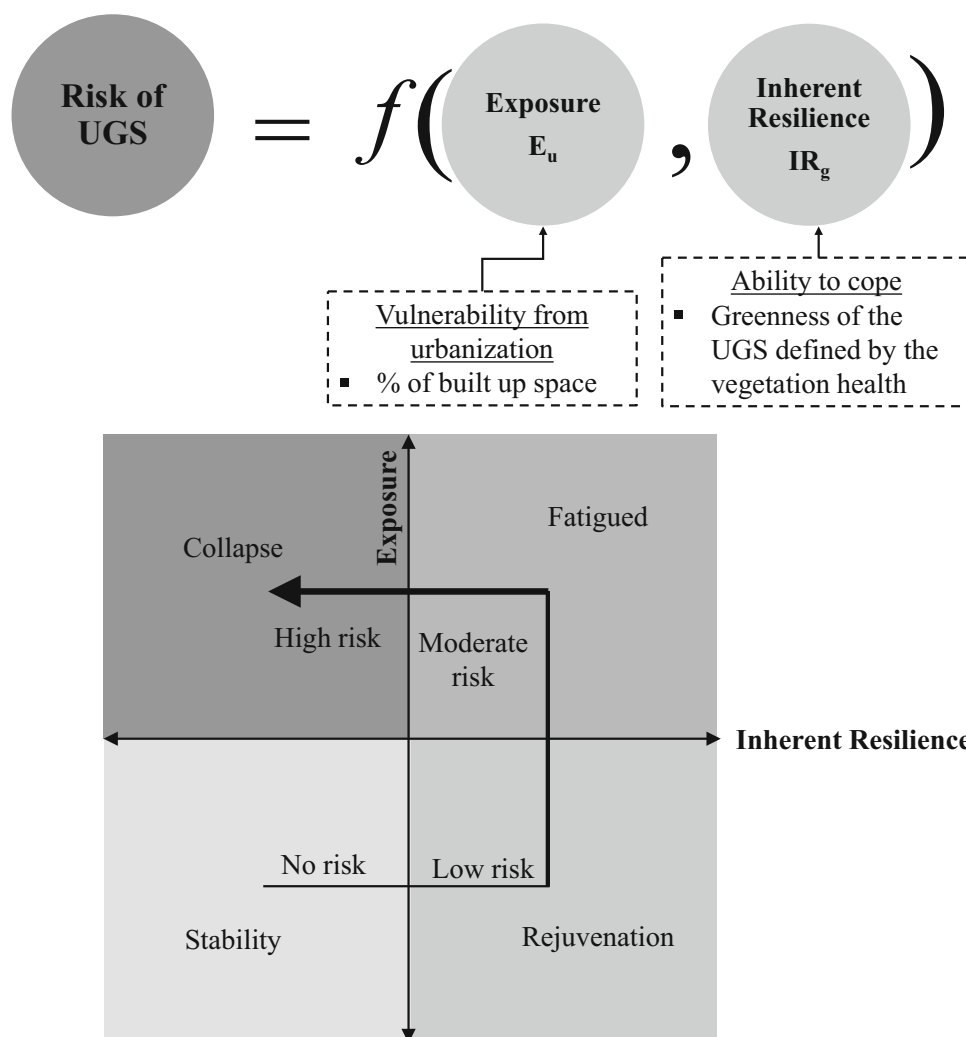
the inherent resilience (IR_g) of the green spaces based on its vegetation health. When E_u exceeds the value of IR_g then the green space is at more risk and vice versa. Conceptually, urban risk susceptibility can be categorized into four basic stages namely: Stable, Rejuvenation, Fatigued, and Collapse. These four stages are depended on the combined effect of level of exposure to the stress and the inherent resiliency. Figure 1 illustrates the conceptual framework of assessing the risk susceptibility of UGS.

Methodology

Data used

To identify the various parameters for UGS vulnerability, indices based classification of remotely sensed data from Indian Remote Sensing Satellite (IRS), Resourcesat-1 IRS P6 Linear Imaging Self Scanner (LISS-IV) (May, 2011) was used. It was then used to classify the UGS based on

Fig. 1 Conceptual framework for assessing risk of urban green spaces



their greenness (vegetation health) into Very High (VH), High (H), and Low (L) values. LISS-IV is a multispectral high resolution sensor with a spatial resolution of 5.8 m at nadir and operating in three spectral bands 0.52–0.59, 0.62–0.68 and 0.76–0.86 μm of green, red and near infrared regions (NIR) of the electromagnetic field. NIR is extensively used for the characterization and identification of vegetation using the Normalized Difference Vegetation Index (NDVI) (Gupta and Jain 2005).

ERDAS Imagine 2013 was used for extraction of the indices pertaining to green cover and built-up areas from LISS IV. Spatial analysis and clustering was performed using, ArcGIS v10.2.2 and GEODAPackages. A Grid cell of 20 m \times 20 m was overlaid over the study area to capture the spatial arrangement of UGS with respect to built-up spaces and to derive two indices, namely: Normalized Built-up Index (NBI) and Normalized Green Index (NGI). The 20 m \times 20 m grid cell was chosen by considering the minimum mapping unit of LISS IV data of 3 pixel by 3 pixel, as derived by the experimental work of Knight and Lunetta (2003) and the premise that the average distance between buildings was 20 m. These cells were assigned with the classified NDVI and built-up area values (refer “Characterization of NDVI and extraction of built-up area”). The detailed methodology is illustrated in Fig. 2.

Characterization of NDVI and extraction of built-up area

NDVI of the UGS was characterized into Very High (VH), High (H), and Low (L) values. It was calculated from the LISS IV data set using Eq. (1).

$$NDVI (LISSIV) = \frac{(Band\ 3\ (NIR) - Band\ 2\ (R))}{(Band\ 3\ (NIR) + Band\ 2\ (R))}, \quad (1)$$

where, *NIR* = near-infrared bands (0.62–0.68 μm) of Band 3, *R* = red bands (0.52–0.59 μm) of Band 2.

It should be noted that NDVI is a representation of the degree of greenness of a particular remote sensing scene and is equal to the chlorophyll concentration i.e., all observed areas having chlorophyll density. It varies with the degree of absorption of red light by plant chlorophyll and the subsequent reflection of infrared radiation by moisture in the leaf (Bhandari et al. 2012). Therefore, NDVI of an urban area depicts both accessible and non-accessible green spaces, however, the city green area in terms of land use only reports the accessible green spaces like parks, playgrounds, gardens, etc. Consequently, the total greenness reported by NDVI image will be much higher than the green cover of land use maps. NDVI values range from +1 to –1, where values near to +1 denotes healthy vegetation, whereas values near to –1

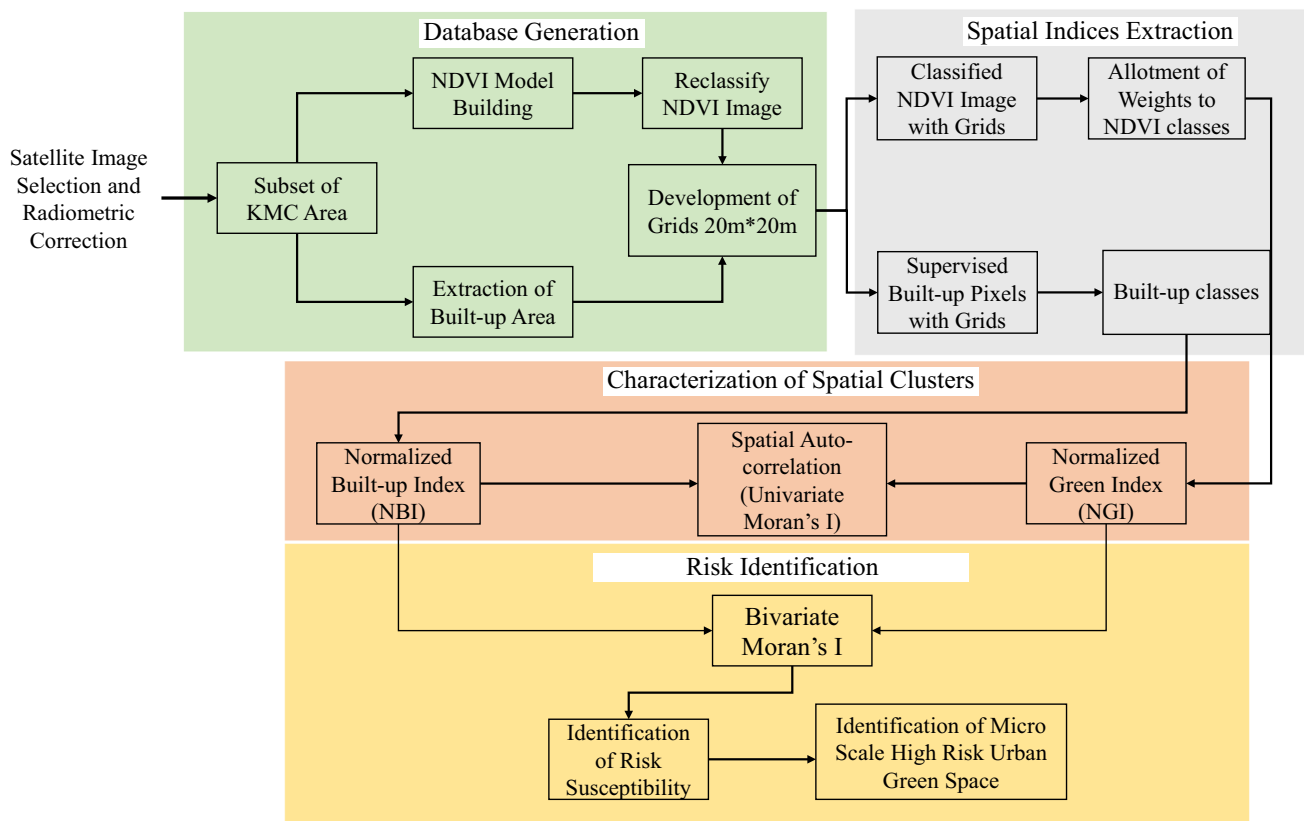


Fig. 2 Adopted methodology

Table 1 Classification of NDVI data and its interpretation

| Segments | NDVI threshold values | Interpretation |
|----------------|-----------------------|---|
| Very high (VH) | >0.6 | Very dense and highly vigorous vegetation |
| High (H) | 0.4–0.6 | Abundant and vigorous vegetation |
| Low (L) | 0.2–0.4 | Sparse and apathetic vegetation |

denotes barren land. This range of +1 to −1 is dependent on the sensitivity of the NIR band of a specific sensor of the satellite (Carlson et al. 1994).

In this study, we divide the NDVI threshold values into three segments: Very High (VH), High (H), and Low (L); which are the subjective representation of the density distribution of vegetation health, as illustrated in Table 1. The values <0.2 were not considered, as it represents non green features like water body. The area of each class of the classified NDVI image was calculated using Eq. (2).

$$\begin{aligned}
 &Area(km^2) \\
 &= \frac{Number\ of\ pixels\ of\ each\ class * (Resolution\ of\ the\ pixel)^2}{10^6}.
 \end{aligned}
 \tag{2}$$

The next step involved the extraction of the built-up area from the LISS IV data, by using the parametric maximum likelihood approach based supervised classification method. Supervised classification is based on the idea that the user can select maximum training samples from the image that are the representative of a specific class and then process the training sets (signatures). These training sets were used as references for the classification of all other pixels in the image. However, the accuracy of this classification is highly dependent on the number of the training sets that were used.

In our classification, we have taken 50 signatures for both built-up and non-built up classes. Finally, the LISS-IV imagery was classified into two classes (1) ‘Built up’ and (2) ‘Non-built up’ with an overall kappa accuracy of 96 %. The raster output from NDVI and built-up areas were co-registered and subtracted from each other (i.e., built-up areas -NDVI). This was done to remove overlapping pixels, such that built-up areas do not have pixels that also represent green vegetation. The threshold for retaining the pixels in the NDVI image, in spite of overlap with built-up area image was set at 0.2.

Development of the normalized green index (NGI) and normalized built-up index (NBI)

In order to quantify the status of UGS based on the NDVI characterization (see Table 1), weights were allotted to each class of the NDVI image, within a range of 1–5. The weights provided are 5, 3 and 1 for Low (L), High (H) and Very High (VH) NDVI classes, respectively. These

weights were provided based on the inherent reliance of urban greens i.e., more NDVI means healthy vegetation and hence more inherent resilience. In other words less is the risk susceptibility. However, no weights were allotted to built-up pixels.

This weighing scheme was utilized for the calculation of the Normalized Green Index (NGI) and the Normalized Built-up Index (NBI), as represented in Eq. (3) and Eq. (4).

$$NGI = \frac{\left[\left(\frac{5*(VH)NDVI\ pixels}{grid} \right) + \left(\frac{3*(H)NDVI\ pixels}{grid} \right) + \left(\frac{1*(L)NDVI\ pixels}{grid} \right) \right]}{\left(\frac{Total\ number\ of\ pixels}{grid} \right)}.
 \tag{3}$$

$$NBI = \frac{Number\ of\ Built\ up\ pixels/grid}{Total\ number\ of\ pixels/grid}.
 \tag{4}$$

Spatial relationship between NGI and NBI

The spatial clustering status with respect to the hot and cold spots of the NGI and NBI within the urban fabric of the study area, was analyzed using univariate local Moran’s I. The local Moran’s I index is one of the most popularly used method for hotspot or spatial cluster identification. It examines individual locations, enabling hotspots to be identified based on a comparison with the neighboring samples, local Moran’s I was calculated using Eq. (5) (Zhang et al. 2008).

$$I_i = \frac{z_i - \bar{z}}{\sigma^2} \sum_{j=1, j \neq i}^n [w_{ij}(z_j - \bar{z})].
 \tag{5}$$

where, z_i represents the value of the variable z at location i ; \bar{z} is the average value of z with the sample number of n ; z_j representing the value of the variable z at all the other locations (where $j \neq i$); σ^2 is the variance of variable z ; and w_{ij} is a weight which can be defined as the inverse of the distance d_{ij} among locations i and j . The weight of w_{ij} can also be determined using a distance band; samples within a distance band are provided with the same weight, whereas samples outside the distance band are given the weight of 0.

Moran’s I value ranges from −1 to +1, where +1.0 indicates clustering while a value near −1.0 indicates dispersion. A high positive local Moran’s I value infers that the location under study has similar high or low values as its neighbors, thus the locations are spatial clusters. The

high–high clusters where, high values are surrounded by high value neighborhoods, and low–low clusters have low values surrounded by low value neighborhoods. In this study, high–high NGI and NBI values depict hotspots of healthy UGS and high urbanization respectively.

Calculating risk susceptibility of USG

To characterize the risk of a particular UGS we use the neighboring NBI values as its level of exposure from urbanization and the NGI values as the inherent resilience. The values of these two variables, the NGI and NBI were then spatially correlated using bivariate LISA to detect the clusters of local risk susceptibility of the USGs (Anselin et al. 2002). Bivariate LISA enables in detecting exact location of spatial clusters of two variables that are spatially autocorrelated (i.e., the extent to the value of one variable at a certain location associates to the value of the other variables in the neighboring locations). The bivariate LISA can be defined as (see Eq. (6)):

$$I_{kl}^i = z_k^i \sum_j w_{ij} z_l^j \quad (6)$$

where, x_l and x_k are the two variables. In this case, they were NBI and NGI. This statistic gives an indication of the degree of linear association (positive or negative) between the value of one variable at a given location i and the average of another variable, at the neighboring locations such as j_s , also known as spatial lag of j (Matkan et al. 2013). Statistically significant similarity (i.e., say CI 95 %) indicates spatially similar clusters in two variables. Here, we considered NGI values as the ‘ x ’ surrounded by the built-up pixels of NBI as the ‘ y -lag’. To understand the spatial distribution of UGS at risk, we categorized the risk zones into four categories based on their values and a corresponding weight was provided to indicate the USG-Urbanization risk susceptibility, as illustrated in the Table 2.

This table should be read as following: if the NGI value of a particular patch of USG is ‘HIGH’ and its surrounding values of NBI is also ‘HIGH’, then the greenness status of that particular green patch is “fatigued” with a ‘MODERATE’ risk susceptibility. That means the green patch has higher resilience, to cope with the high exposure from NBI, however, the green patch is fatigued i.e., with prolonged exposure it might collapse. Similarly, when NGI value is ‘LOW’ and the neighboring NBI value is ‘HIGH’, then the risk susceptibility is very high, i.e., exposure from urbanization exceeds inherent resilience and hence will evidently lead to collapse of the green space.

Since the risk susceptibility values were subjectively measure, for ease of calculation we convert them to objective values by assigning weights in accordance to their hierarchy of risk susceptibility.

Identification of exposure quotient of USG and specific green assets under maximum risk

Deriving from the conceptual framework, we assume the risk of UGS as a scalable factor of exposure and inherent resilience. To identify the exposure of the green spaces from urbanization, which need immediate attention, we divided the risk susceptibility weights with the inherent resilience of USG (NDVI weights) to construct an exposure matrix. The premise of this identification process is based on the fact that if the inherent resilience is ‘HIGH’, even under the highest risk susceptibility, the green space might survive, but will remain in a state of fatigue. Table 3 illustrates the exposure matrix.

Finally, to identify specific urban green assets like trees or small patches of green spaces at maximum risk at the grid level (20×20), we used the following step-wise algorithm. The algorithm first picks all the grids from NGI which has a value between 0.2 and 0.4, then from these selected grids only those grids that have a risk susceptibility of seven were carefully chosen. Finally, from these selected grids only those grids that had NBI more than 0.5 were selected. These selected grids represent the micro-level green patches at highest risk (Fig 3).

Study area

The megacity Kolkata, formerly known as Calcutta, is the densest city of the world. It has a population density of 24,718 per sq km, accommodating 4.5 million inhabitants in 141 census wards (Census 2011). The Kolkata Metropolitan Area (KMA) area comes within 22.001’ to 23.019’ North Latitude and 88.004’ to 88.033’ East Longitude, within which KMC is located between 22.030’ to 22.037’ North Latitude and 88.018’ to 88.023’ East Longitude (KMDA 2006). Once, the colonial capital of India, the impact of colonialism is deeply embedded in the city’s spatial structure and socio-cultural realm. The current spatial structure includes high population density, a compact design, and a widespread network of public/intermediate public transport (IPT) with inadequate road infrastructure (6 %) (Census 2011). During 1950–1970 s, this city had beheld heavy working class migration, leading to a severe shortage of housing, food, sanitation and hygiene, and proper healthcare. As the countermeasure, the government sought of expanding city limits and design, the newly expanding city into ‘compact-CBD’ like zones. However, this failed due to lack of ‘developmental’ synergies between the new ‘compact-CBD’ and the original CBD of Kolkata (basically, the older part of the city). This led to the creation of “multiple compact poly-centres”, in

Table 2 Risk susceptibility classification

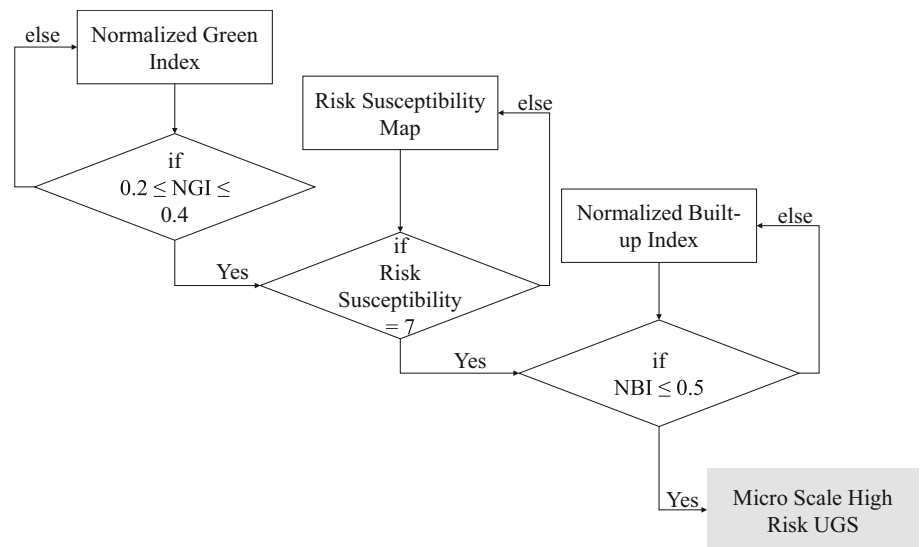
| NGI (x) | NBI (y-lag) | Risk susceptibility of UGS | Status of NGI | Weight |
|---------|-------------|----------------------------|---------------|--------|
| HIGH | HIGH | Moderate | Fatigued | 5 |
| LOW | LOW | No | Stable | 3 |
| LOW | HIGH | High | Collapse | 7 |
| HIGH | LOW | Low | Rejuvenation | 1 |

Table 3 Exposure matrix

| Inherent resilience of USG (NDVI weights) ↓ | Risk susceptibility weights → | | | |
|---|-------------------------------|------|------|------|
| | 7 | 5 | 3 | 1 |
| 5 | 1.40 | 1.00 | 0.60 | 0.20 |
| 3 | 2.33 | 1.60 | 1.00 | 0.33 |
| 1 | 7.00 | 5.00 | 3.00 | 1.00 |

These values were then spatially plotted to generate an exposure surface map of the USGs

Fig. 3 Process for identifying grid level UGS risks



the ‘Development Perspective and Investment Plan of 1976’, with the objective of ease the pressure of the high population density from the original CBD and create high-density green fields (Bardhan et al. 2015). However, this is yet to be achieved and is further is emulated in the ‘VISION-2025’ of the Kolkata Metropolitan Planning Committee (KMPC) (KMDA 2006). This study aims to be an aiding tool in designing UGSs to attract more people into the planned compact poly-centres, and cater to the overall inclusive development of the City of Joy: Kolkata (see Fig. 4).

Land-use status (2008)

Nath and Acharjee (2013) estimated the land-use pattern of Kolkata Municipal Corporation (KMC) as 19411.08 hectares or 194.11 sq. km in 2008, from Google Earth high resolution satellite data. The percentage land use change in

the KMC zone for the year 1900, 2000, 2004 and 2008 is illustrated in Fig. 5.

Results

In this study, we had used NDVI based urban greenness mapping, to demarcate the Kolkata’s vegetation health. This was the first step towards the identification of UGS which are the most and least resilient to urbanization. Figure 6 and Table 4 illustrates the NDVI based UGS classification which denotes the degree of greenness (vegetation health).

In order to define the spatial clustering of NGI and NBI values, univariate local Moran’s I was calculated. Moran’s I value was found to be 0.550 for NGI variables, indicating significantly high clustering. Whereas, Moran’s I value of NBI was 0.720 representing a high correlation between

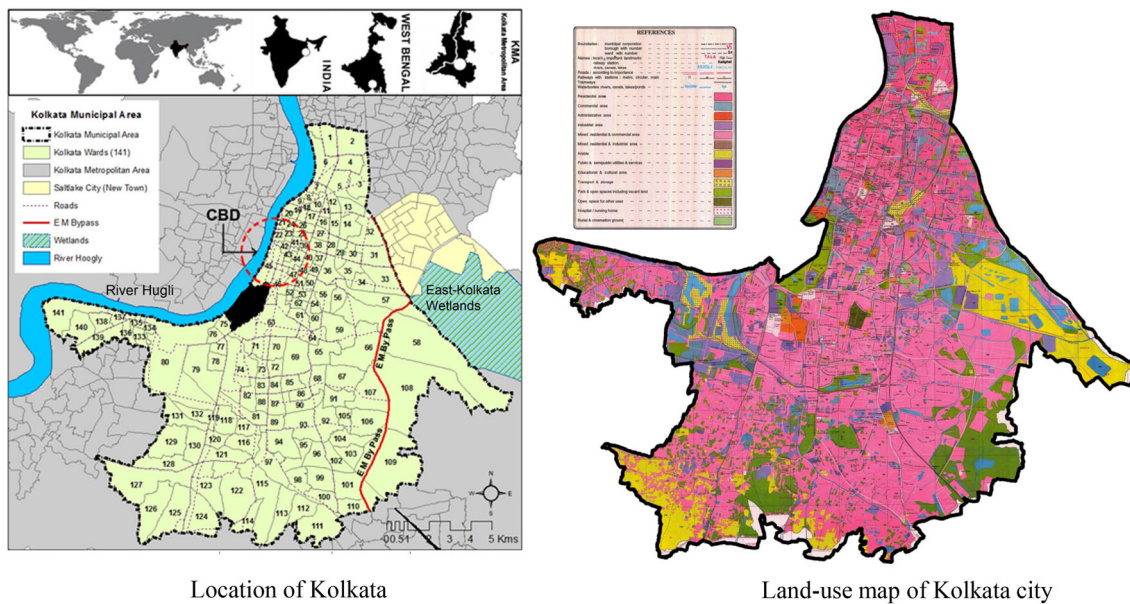


Fig. 4 Map of the study area Source: Bardhan et al. (2015)

built-up clusters. Thus, supporting the high-density of Kolkata, see Table 5.

The bivariate Moran's I of $NGI(x)$ and NBI (*lag of y*) was -0.393 . The negative value implied an inverse relationship between NGI and NBI . This infers that the low green-spaces are surrounded by high built-up areas.

Discussion

In this study, a conceptual framework was forwarded to identify urban green spaces that are at high risks due to urbanization. This framework will be an essential tool to urban planners and policy makers to facilitate sustainable urban built environment bye-laws and guidelines. The risk susceptibility of the UGS was calculated using $NDVI$ values, classified into three categories: Low (L), High (H) and Very High (VH). In order, to convert this subjective measure into an objective measure, weights were assigned. This objective measure was termed as NGI . This $NDVI$ of Kolkata is illustrated in Fig. 6. Following steps included, deriving the spatial relationships between NGI and NBI , and finally converging the spatial correlations, into USG 's risk susceptibility index by using bivariate Moran's I .

The risk susceptibility of the UGS in Kolkata is illustrated in Fig. 7. The red and blue colors imply regions which need immediate attention in terms of UGS protection and conservation measures, whereas green and yellow areas represent the risk in a decreasing order of low to no risk. Based on the conceptual framework (see Fig. 1), it can be inferred that the red and blue areas are the zone of UGS

collapse and fatigued respectively, whereas the yellow zone are areas that have the potential to regenerate or rejuvenate. However, the green zones are the areas that are most stable, i.e., will survive from the stresses of rapid urbanization.

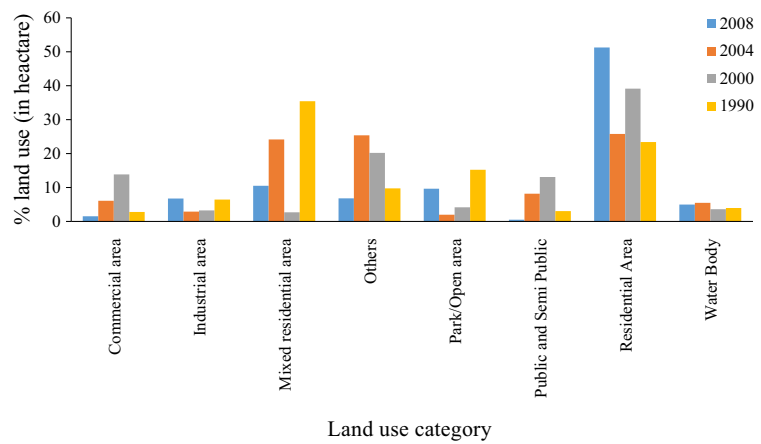
To precisely identify which trees or green patches need immediate attention, micro-scale green space analysis of UGS was carried out using the three-step algorithm (see Fig. 3). It is evident that the rapid urbanization poses high risk to the UGSs both at a macro and micro level. Although, the micro-level dynamics might tend to associate with the socio-economic and urbanization speculation dimensions of the city. Figure 8 illustrates the micro-level risk UGSs.

If we look at the spatial distribution of the green spaces at moderate to high risks, it can be seen that more risk inclined green spaces are concentrated in the North, West and the central part of the city, where the consolidation of built-up spaces are high, as illustrated in Fig. 7. The Southern and the Eastern part of the city pose less risk on account of the wetlands. The highest susceptibility of UGS were found to cluster in the Northern part of the city, which are the older parts of the Kolkata city. These areas have high sprawling due to heavy urbanization, thus, consequently manifesting in high risk susceptibility for the green spaces.

Conclusion

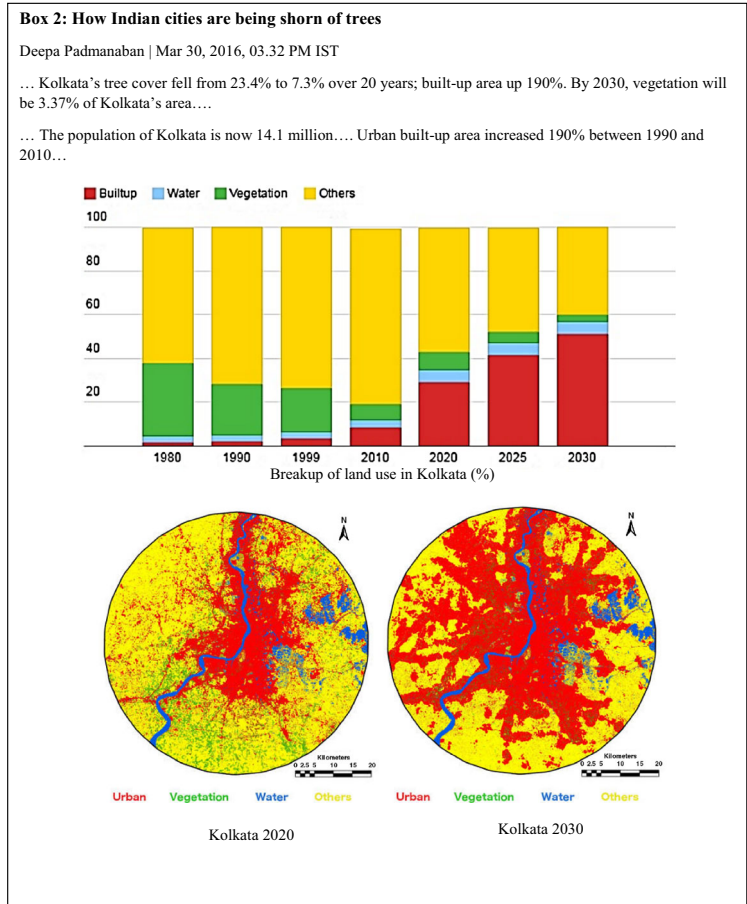
Uncontrolled urbanization in India is the biggest driver of rapid environmental and green space degradation. (Maiti and Agrawal 2005). The urban heat island effect is also another outcome of rapid green asset degradation, which is

Fig. 5 Land use status in percentage [Source: Nath and Acharjee (2013)]



Box 1: Greying Kolkata's green cover in free fall
 Krishnendu Bandyopadhyay | TNN | Apr 14, 2015, 12.38 AM IST
 ... Recent satellite picture analysis has revealed that Kolkata's green cover has dipped to an extremely unhealthy 4.79%... the minimum requirement for an Indian city is 15%....
 ... According to the National Commission on Urbanization, Less than 1% of city space now remains vacant...
 ... A research conducted by Netaji Subhas Bose Open University... Ward 19 has 42% and Ward 20 has 58% vegetation area but a sharp drop in vegetation density increased environmental risks like pollution and global warming.

Source: (Bandyopadhyay, 2015)



Source: (Padmanaban, 2016)

Fig. 6 Classification of UGS based on NDVI values Source: (Bandyopadhyay 2015)

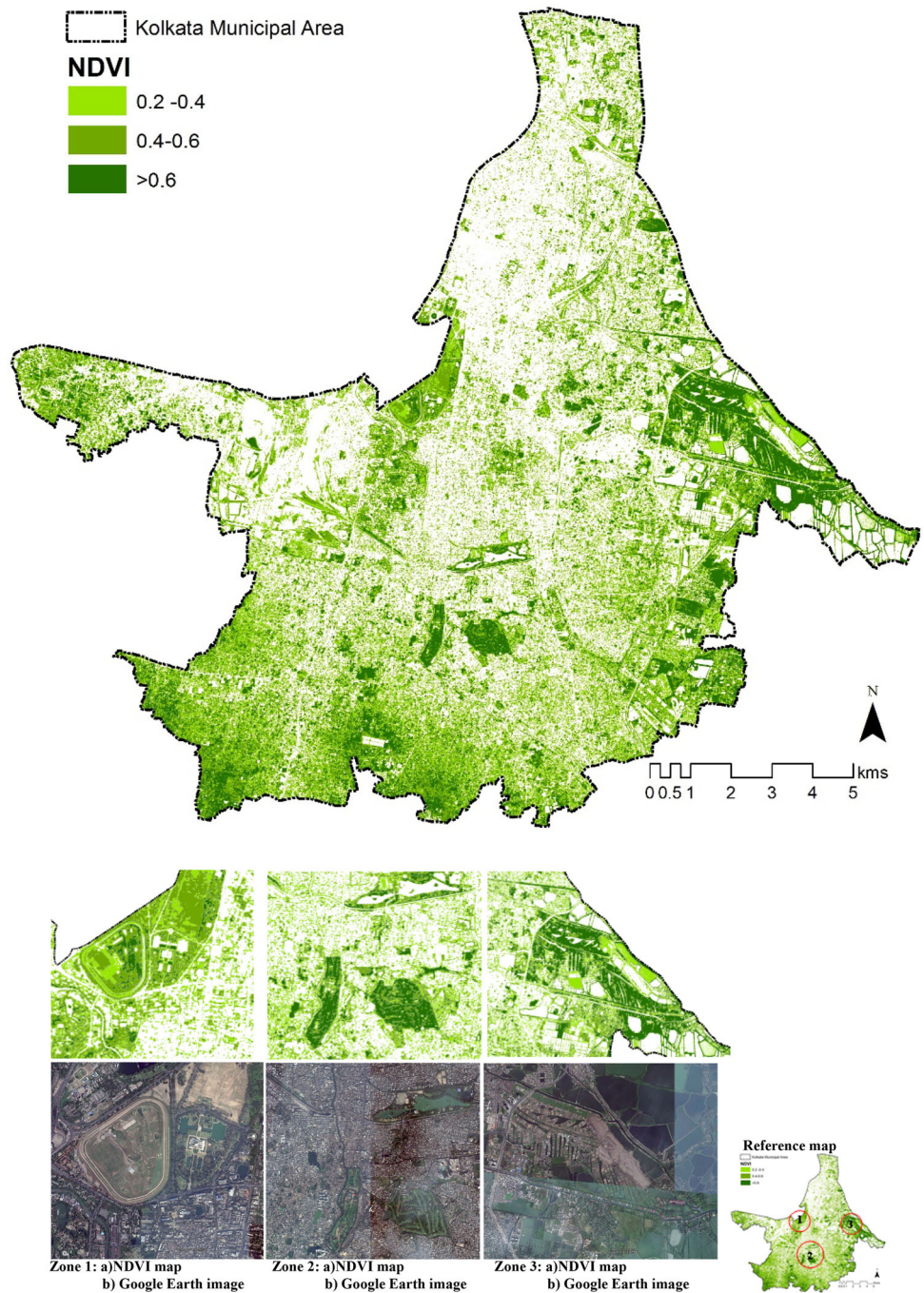


Table 4 Classification of UGS based on its vegetation health

| NDVI values | Area (km ²) | Percentage (%) | Inferences ^a |
|----------------|-------------------------|----------------|-------------------------|
| Low (L) | 41.26 | 44 | Collapsing UGS |
| High (H) | 33.81 | 36 | Fatigued UGS |
| Very high (VH) | 18.67 | 20 | Rejuvenating UGS |

^a These inferences are in terms of the conceptual framework

Table 5 Descriptive of different classes of UGS

| NDVI value | Normalized Green Index (NGI) | |
|----------------|------------------------------|--------------------|
| | Mean | Standard deviation |
| Low (L) | 0.29 | 0.07 |
| High (H) | 0.50 | 0.06 |
| Very high (VH) | 0.73 | 0.09 |

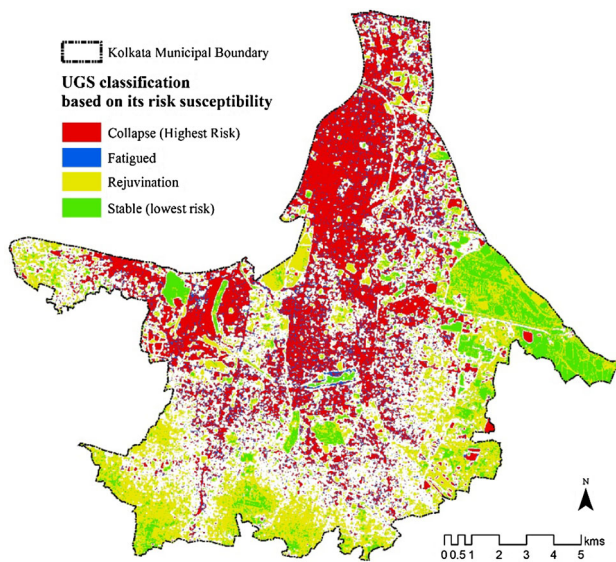


Fig. 7 Risk susceptibility of UGS

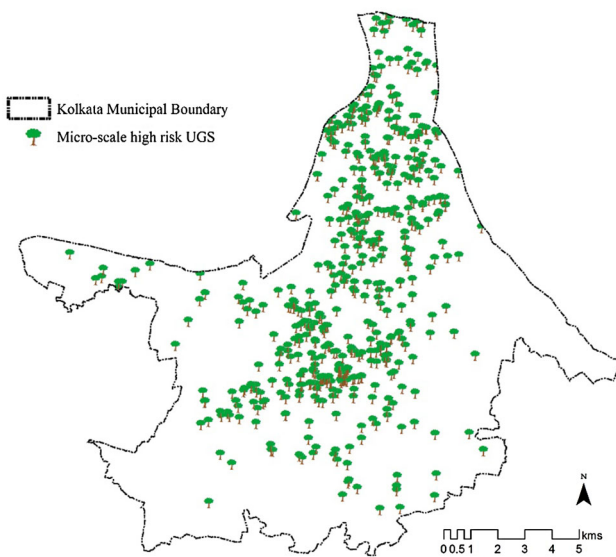


Fig. 8 Micro-scale high risk susceptibility mapping of UGSs

shrinking the scope and boundaries for energy and health sustainability. Green spaces are the most essential component of the built-environment. The presence of green spaces not only improves health, social well-being, but mitigates the ill-effects of climate change (Tu et al. 2016). Thus the green spaces cater to every normative layer of sustainable urban development. It is an utmost necessity to preserve and protect the green spaces in the city to foster inclusive growth. However, urban planners and policy makers, lacks appropriate tools to identify and solve the resource allocation problems associated with the UGS design. This study demonstrated that remote sensing technology when coupled with GIS tools, can be a valuable

technique towards identification and monitoring of green spaces that are at high risks. Future work lies in the refinement of the spatial data using LIDAR or other advanced high resolution satellite imagery systems, so that more realistic models can be analyzed at the neighborhood and individual level.

In diverse megacity like Kolkata, it is extremely difficult to find spaces for the development of UGS. Moreover, the current green spaces are at the brink of extinction due to rapid urbanization and population explosion. The methodology that is forwarded in this study, not only assess the state of UGS in the built environment of the city, but also pin-points high risk zones. This quarantine of high risk UGSs, can help in efficient resource allocation by the policy makers. This tool enables the planner to focus on green assets at a micro- level, thus, enabling a bottom up planning strategies. The conceptual framework which is devised in this study for the quantification of the green space can be applied to other Indian cities, where the process of urbanization is fast and urban greens is stressed. Due to its low resource intensity and ease of computation, this method can be easily adopted by planners and policy makers for sustainable development and rapid planning process for any developing nations. Therefore, fostering more community engagement and nurturing pro-environmental behavior among the habitants. Strengthening the green cover right from the household to the neighborhood to city level, which will not only stabilize the environmental degradation and climate change, but will also push the community and the country towards fulfilling the UN-Sustainable Development Goals.

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