MULTISCALE ANALYSIS OF THE RELATIONSHIP BETWEEN SOCIO-ECONOMIC STATUS (SES) AND REMOTELY SENSED SPATIAL PATTERNS OF URBAN GREEN SPACES (UGS) IN MUMBAI, INDIA.

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ABSTRACT: The lack of necessary policy interventions in the cities of the developing countries result in a disproportionate distribution of Urban Green Spaces (UGS), a key component of urban landscape. The socio-economically affluent neighbourhoods are known to possess a better share of UGS arranged in distinctive spatial patterns. Studies relating Socio-Economic Status (SES) and UGS often overlook the aspect of spatial arrangement of UGS; this dearth in quality information on UGS can be addressed using remote sensing. With synoptic coverage in a near-real time, remote sensing systems aid the computation of spatial metrics that capture the compositional and configurational aspects of UGS. However, as the spatial metrics are scale-dependent, the relationship between SES and spatial metrics is susceptible to the spatial resolution of the satellite imagery chosen. In this study, the scale effects of the Modifiable Areal Unit Problem (MAUP) on the links between SES and the spatial metrics characterizing UGS are assessed using satellite images of multiple spatial resolutions, viz. 5m, 15m and 30m. SES of the neighbourhoods in Mumbai was assessed using the Socio-Economic Status Index (SESI), based on which the neighbourhoods were classified into different SES classes. UGS in Mumbai were extracted from the satellite images, and the aspects of density, shape complexity and aggregation of the UGS patches at the neighbourhood level were each quantified with a spatial metric. An ordered logistic regression (OLR) was used to assess the probabilistic association between SES and the spatial metrics. A resolution-wise comparison of OLR results reveals that the relationship between SES and the spatial metrics is indeed influenced by the spatial resolution of the satellite image chosen. The study results equip the urban planners with a tool in form of remote sensing-based spatial metrics of UGS to reliably predict the SES of a neighbourhood in a shorter time.

1. INTRODUCTION

The cities in the developing countries often see little or no urban planning interventions (M'Ikiugu *et al.*, 2012). The rapid pace of urbanization in these cities results in a spatially skewed distribution of natural, social, and economic resources, which influence the quality of urban life (QoUL) of its residents (Cohen, 2006; UN, 2013). One such vital component influencing the QoUL is the Urban Green Spaces (UGS). UGS refer to all the vegetation spaces that add value to the urban landscape (Bardhan *et al.*, 2016), and are known to enhance urban environmental quality by reducing pollution (Gupta *et al.*, 2012), improve public health (Groenewegen *et al.*, 2006), and are vital in mitigating urban vulnerabilities (Bardhan *et al*., 2016). The distribution of such highly beneficial UGS is generally lopsided, with the neighbourhoods habituated by the socio-economically weaker sections having a fewer green space per inhabitant (Heynen *et al*., 2006; Krellenberg *et al*., 2014). This disparity in distribution and configuration of UGS among the neighbourhoods belonging to different socio-economic status (SES) is starker in the cities of the developing countries, given the lack of necessary planning interventions (De la Barrera *et al.*, 2016).

In general, the studies linking UGS and SES use the highly time-consuming and expensive survey-based methods to collect self-reported assessments of UGS (Gupta *et al*., 2012*).* Also, these studies in general confine their assessment of UGS to the mere presence/absence of green cover in an area (see for example: Gascon *et al*., 2016) or the proximity of UGS to a neighbourhood (see for example: Krellenberg *et al*., 2014), often ignoring the spatial configuration of the UGS. These pitfalls can be overcome with the help of remote sensing. Using the remotely sensed satellite images, which offer a repetitive, synoptic coverage of the landscape in a near-real time, the spatial configuration of UGS can also be computed by means of indices called spatial metrics (SM) (Huang *et al*., 2007). Thus, the application of remote sensing can add the dimension of spatial arrangement, thereby enhancing the information on UGS available to the urban planners. For example, Sathyakumar *et al* (2017) have used satellite images of 5m spatial resolution to identify the relationship between the SM of UGS patches and the SES in the neighbourhoods of Mumbai, whereby the neighbourhoods with higher SES are associated with highly disaggregated and complex-shaped UGS patches.

However, it is well known that spatial metrics, similar to other spatial data, are prone to the scale effects of Modifiable Areal Unit Problem (MAUP), by which the spatial patterns studied are affected by the changes in the level of data aggregation (Shen *et al*., 2004; Buyantuyev *et al*., 2010). The scale effects on spatial pattern analysis occur under three scenarios: i) change in resolution (or grain size) only, ii) change in extent only, and iii) change in both resolution and extent (Wu, 2004). This implies that the nature of relationship between SES and the SM of UGS may be found to vary significantly at different spatial resolutions of the remotely sensed satellite images used.

In this purview, the present study builds on the work described in Sathyakumar *et al* (2017) by investigating the impact of the changing scales on the relation between the SES and the SM of UGS patches in the neighbourhoods of Mumbai. Since the extent of analysis is fixed as Mumbai, only the effects of changing the spatial resolution is studied in the present work, using the satellite images of multiple spatial resolutions, viz. 5m, 15m, and 30m, which are commonly used worldwide for urban applications (Qian *et al.*, 2015).

2. STUDY AREA

Mumbai, the financial capital of India, hosts approximately 12.4 million people (Census, 2011), and is spread across 458.28 sq km (MCGM, 2016). The city is divided into 88 Census Sections (CS) and comprises two revenue districts- Mumbai City and Mumbai Suburban. The Suburban District accounts for about 75% of the population of Mumbai (Census, 2011), and has been a part of the city since the 1950s *(*Pacione, 2006). The civic administration of the city is catered by the Municipal Corporation of Greater Mumbai (MCGM). Urban planning of Mumbai is widely under the ambit of MCGM, which designs the Development Plans (DP) periodically. However, out of the two DPs constituted in 1967 and 1991, only 35% have been actually implemented (MCGM, 2016). As a result, much of Mumbai's current land use is organic, and hence, inconsistent with the planned one (Pethe *et al*., 2014).

A particularly key issue in the planning of Mumbai is affordable housing. The city attracts a massive influx of migrants from economically weaker sections from across the country in search of employment with minimal expenditure on accommodation and subsistence (Pacione, 2006*)*. However, the high prices of housing stock in the city makes them choose informal settlements, like slums, for dwelling (Bardhan *et al*., 2015a). As a result, about 42% of Mumbai's population in 2011 lived in slums, which are located mainly along creeks, railway lines, the periphery of hills and forests (MCGM, 2016*)*. At the intra-city level, the proportion of slum population to the total population is 27.87% and 46.46% for the City and Suburban districts respectively (MCGM, 2016). This indicates the relatively better socio-economic status of the city district vis-à-vis the suburban district.

Mumbai's geography consists of a national park (the Sanjay Gandhi National Park, SGNP) in north, and mangroves along its eastern and western shores. Its coast is habituated by fisherfolk, who live in hamlets called '*Koliwadas'*. These *Koliwadas* are located mainly in the north western part of the western suburbs, and are particularly known to lack basic civic amenities (Baud *et al*., 2009). The city also contains a few lakes, hillocks and ridges, specifically in the eastern suburbs. Apart from these and a few parks, Mumbai's urban green spaces are scarce given the limited availability of land area (MCGM, 2016).

3. DATA AND METHODS

The study workflow (Fig. 1) comprises two main components-(i) Assessment of SES, and (ii) Characterization of UGS. The unit of analysis is 'census sections' (CS), a territorial unit used for census operations at the intra-city level and the finest resolution at which the census data is available publicly. The CS can be considered as city neighbourhoods (Bardhan *et al*., 2015b), and there are 88 CS in Mumbai. The data used and detailed methodology of the study are presented in the following sections.

3.1 Data Description

A map of Mumbai's CS classified based on their SES, given by Sathyakumar *et al* (2017), was used as the source of information on their SES, wherein the CS were classified into 5 clusters as Very Low SES (VLS), Low SES (LS), Moderate SES (MS), High SES (HS), and Very High SES (VHS) based on their Socio-Economic Status Index (SESI) scores. SESI scores range from 0 to 100, where 0 and 100 signify the lowest and highest-ranking CS in terms of SES. This map is shown in Figure 2 and the descriptive statistics of these 5 SES clusters is given in Table 1. The boundaries of the CS was prepared in a digital form ("shapefile") using QGIS v2.14.0, based on the maps provided online by the Chief Electoral Officer, Maharashtra State (CEO Maharashtra, 2017).

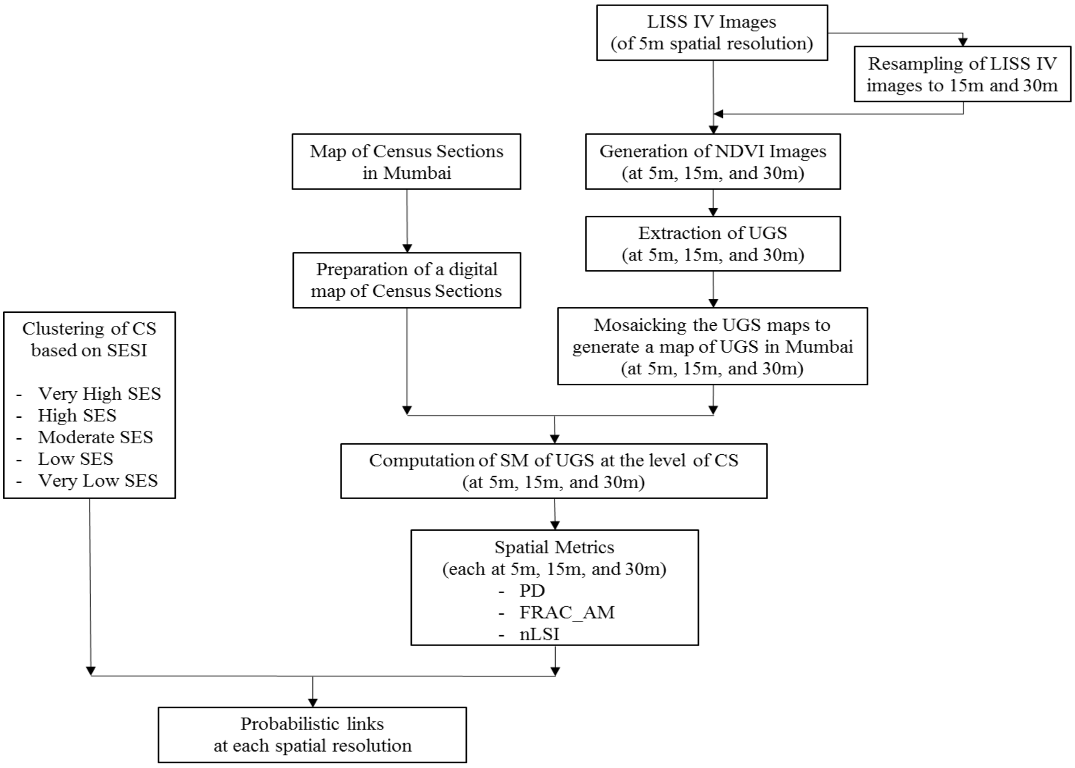

Fig.1. The methodological framework adopted for the study.

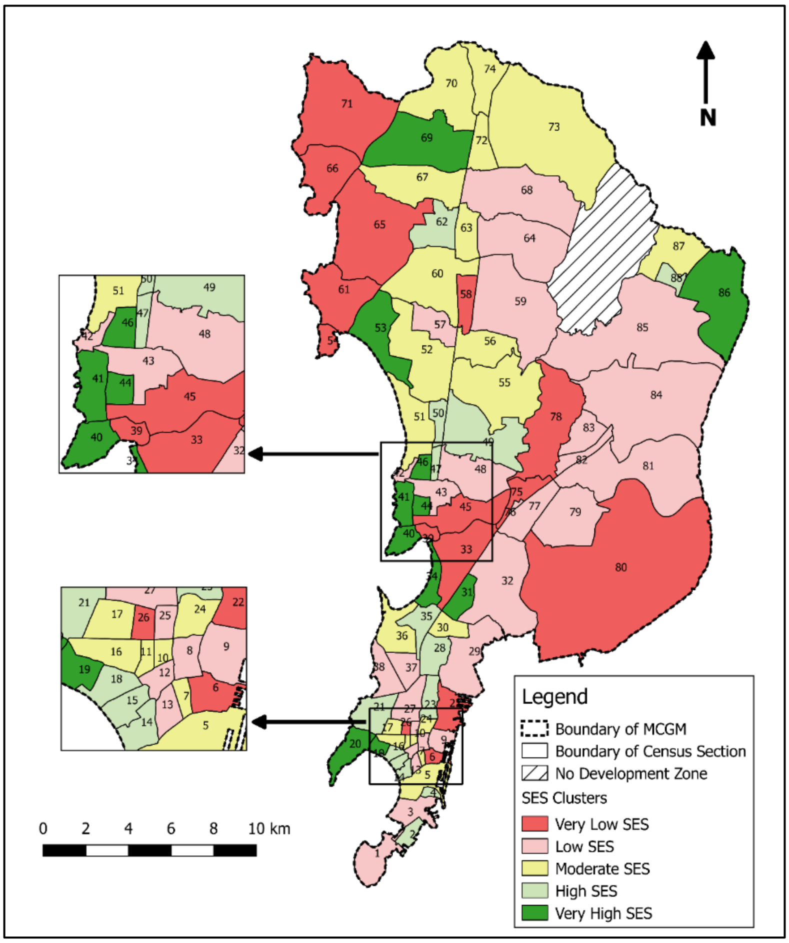

Fig. 2. SES Clusters of census sections in Mumbai.
(Source: Adapted from Sathyakumar *et al* (2017))

Table 1. Descriptive statistics of the SES Clusters (Source: Adapted from Sathyakumar *et al* (2017)).

SES Cluster	N	Median SESI	Std. Dev.	Min. SESI	Max. SESI
Very Low SES (VLS)	15	28.30	9.09	0	35.07
Low SES (LS)	27	47.45	4.79	38.88	53.87
Moderate SES (MS)	21	62.33	3.78	55.60	67.32
High SES (HS)	14	74.32	2.77	70.04	79.79
Very High SES (VHS)	11	86.18	6.04	80.79	100
Total	88	56.20	20.19	0	100

To assess the UGS in Mumbai, a set of three IRS Resourcesat-2 Linear Imaging Self Scanner (LISS-IV) images of 5m spatial resolution were used. The details of these three images are given in Table 2. The LISS-IV images have spectral information in the wavelength ranges of 0.52-0.59µm, 0.62-0.68µm, and 0.77-0.86µm, corresponding to the green, red and Near Infra-Red (NIR) wavelengths of the electromagnetic spectrum. Each of these images partly cover Mumbai, and were acquired during the months of October and November 2011, and are the cloud-free ones of Mumbai acquired closest to the census enumeration period of February 2011. Further, these three images of 5m resolution were resampled to generate two more sets of 15m and 30m spatial resolutions, using the 'degrade' function of the ERDAS Imagine 2014 package. Thus, there were 9 satellite images in total (i.e. three per each of the three spatial resolutions).

Table 2. Details of the IRS Resourcesat-2 LISS IV images used in the study.

Date of Pass	Path ID	Row ID	Sub-Scene
October 10, 2011	94	59	A
November 3, 2011	94	59	B
October 10, 2011	94	59	C

3.2 Characterization of UGS

3.2.1 Extraction of UGS: The urban green spaces (UGS) were extracted using the Normalized Difference Vegetation Index (NDVI), which is calculated as shown in Eq. 1.

$$NDVI = \frac{NIR-Red}{NIR+Red} \tag{1}$$

where *NIR* and *Red* denote the spectral reflectance in Band 3 (0.77-0.86µm) and Band 2 (0.62-0.68µm) respectively. The NDVI values range from -1 to 1, where the pixels with values above 0.2 represent vegetation class (Javadnia *et al*., 2009; Tang *et al*. 2015). Accordingly, a threshold of 0.2 was chosen to extract a binary image consisting of vegetation and non-vegetation pixels from each of the 9 images. These images were analysed individually as they belonged to different dates. Subsequently, the three resultant images for each spatial resolution were mosaicked using the 'mosaic' function of the ERDAS Imagine 2014 package to generate maps of UGS in Mumbai at 5m, 15m and 30m spatial resolutions.

3.2.2 Computation of Spatial Metrics: In this study, three spatial metrics (SM), viz. Patch Density (PD), area weighted mean fractal dimension (FRAC_AM), and normalized landscape shape index (nLSI), were used, that capture the aspects of density, shape complexity and aggregation of UGS patches in a CS respectively. Here, a UGS patch refers to a contiguous group of UGS pixels in a CS, defined by an 8-cell rule (i.e. all the 8 surrounding pixels were considered for patch membership). A description of the three SM used is given in Table 3. The SM were computed at the CS-level from each of the three UGS maps (of different spatial resolutions) using FRAGSTATS v4.2 package (McGarigal *et al*., 2012).

3.3 Probabilistic Analysis between SES Clusters and Spatial Metrics of UGS

The relation between the SES of a CS and the SM of its UGS was analysed using an ordered logistic regression model separately for each of the three spatial resolution cases. In each case, the SES category of a CS was considered as dependent variable while the SM of its UGS computed at that spatial resolution acted as the independent variables. The resultant odds ratio associated with each spatial metric denotes the relative impact of that spatial metric on predicting the SES of a CS. Also, based on the coefficients estimated and the values of the three spatial metrics computed earlier (refer section 3.2.2), the probability of a CS belonging to each of the 5 SES categories was estimated.

Finally, the results of the three models (corresponding to the three spatial resolutions) were compared to assess the relative change in the significance levels of the 3 SM in predicting the SES category.

Table 3. Description of the spatial metrics used (Source: McGarigal, 2015).

Spatial Metric	Formula	Description	Remarks
Patch Density (PD)	PD = $\frac{n}{a} * 100$	where *n* is the number of UGS patches in a CS, and *a* is the area (in ha) of that CS.	Expressed in number of patches per ha of CS.
Area-weighted Mean Fractal Dimension (FRAC_AM)	FRAC_AM = $\sum_{i=1}^{i=n}\left(\frac{a_i}{A}\right)\left(\frac{2\ln 0.25\, p_i}{\ln a_i}\right)$	where *n* is the number of UGS patches in the CS, *A* is the total area of UGS patches in that CS, a_i and p_i denote the area and perimeter of patch *i* respectively.	Unitless; Takes values in range of 1 to 2; 1 signifies simple geometry, whereas 2 signifies a convoluted geometry.
Normalised Landscape Shape Index (nLSI)	nLSI = $\frac{P - min\, P}{max\, P - \min P}$	where *P* is the total perimeter of the UGS patches in a CS; *min P* and *max P* are computed based on the total area of UGS patches in a CS, given as *A*; *min P* represents the perimeter of the UGS patch of area *A* if the patches were maximally compact; *max P* represents the perimeter of the UGS patches with the total area *A*, if the patches were maximally disaggregated.	Unitless; Takes values in range of 0 to 1; 0 signifies that the patches are maximally compact, whereas 1 signifies that the patches are maximally disaggregated.

4. RESULTS AND DISCUSSION

4.1 Mapping of UGS

Three maps of UGS in Mumbai extracted using the NDVI at the spatial resolutions of 5m, 15m and 30m are given in Figures 3, 4, and 5 respectively. In all these maps, the CS in the north-western part of the western suburbs and those adjoining the SGNP are rich in green cover with almost no fragmentation, signifying that vast portions of these CS are not urbanized. The hillocks and mangroves in the eastern suburbs are conspicuous on the map, appearing as composite green blocks. The southern part of the city district, one of the oldest parts of Mumbai, has sparse green cover. Also, the slum neighbourhoods in the city are observed to be devoid of vegetation. In Figures 3, 4, and 5, the UGS maps for the CS numbered 42 (belonging to Low SES) and 46 (belonging to Very High SES) at all three resolutions used are given as insets for comparison purposes. In all these three figures, it can be seen that CS 46 has a higher patch density, more complex-shaped patches, and relatively more disaggregated patches than the CS 42. It is confirmed by their respective PD, FRAC_AM, and nLSI values at all three resolutions. Also, from Figures 3,4, and 5, three major observations can be made as the resolution becomes coarser: i) the smaller UGS patches are not identified, ii) the UGS patches appear to have relative simpler shapes, and iii) the UGS patches appear to be more disaggregated. The non-detection of smaller UGS patches at coarser resolution is understandable given the high degree of heterogeneity in terms of land cover in a hyper dense city like Mumbai (Oyana *et al*., 2014). Hence, the CS 7 at 15m resolution has no identifiable UGS patches, although at 5m resolution five of them are identified. Similarly, at 30m resolution, apart from CS 7, CS numbered 10, 12 and 26 also appear to be devoid of UGS although they had at least one UGS patch each at 15m resolution. The use of a larger window size also smoothens the edges of the UGS patches, thereby making them appear with relatively simpler shapes. Similarly, at coarser resolutions, due to the non-detection of smaller but contiguous green spaces among the greater UGS patches, they appear to be more disaggregated. These observations are confirmed in the mean values of the SM as well (Table 4). As resolution becomes coarser (i.e. 5m to 30m), PD and FRAC_AM decrease while nLSI increases. It is worth noting that the variation of PD across the resolutions should be read in the context of varying definition of a patch in terms of area.

Table 4. Mean of each SM of CS in Mumbai for different spatial resolutions.

Spatial Resolution (m)	Mean of Spatial Metrics for the 88 CS		
	PD (per ha of CS)	FRAC_AM	nLSI
5	166.55	1.276	0.169
15	49.29	1.229	0.284
30	16.55	1.185	0.311

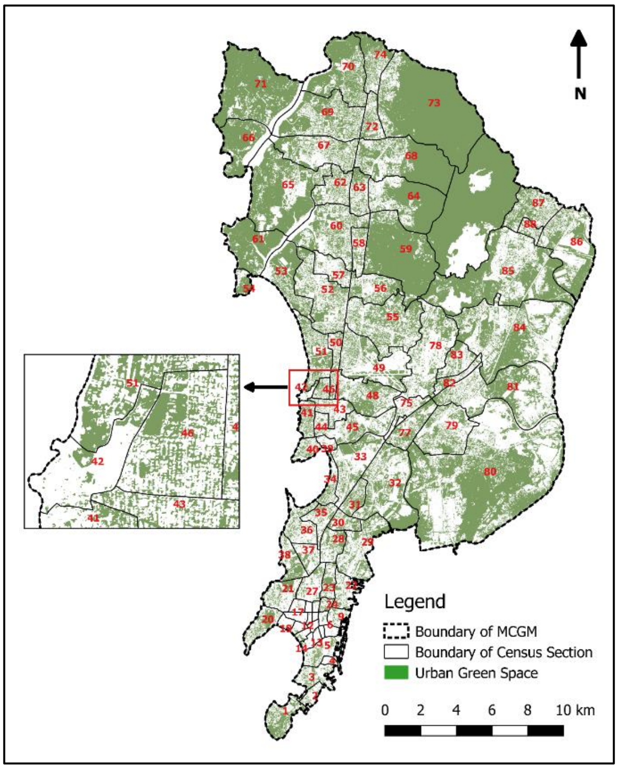

Fig. 3. Map of UGS in Mumbai extracted from satellite images of 5m spatial resolution.

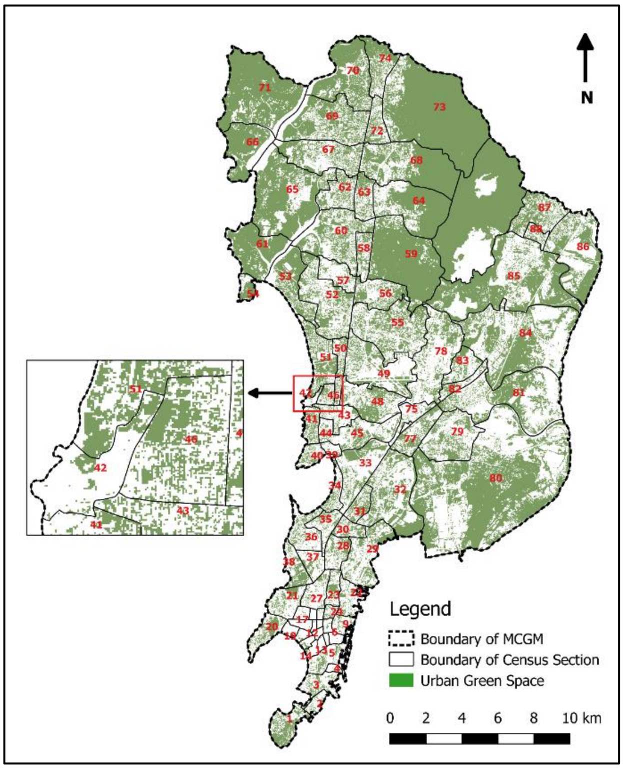

Fig. 4. Map of UGS in Mumbai extracted from satellite images of 15m spatial resolution.

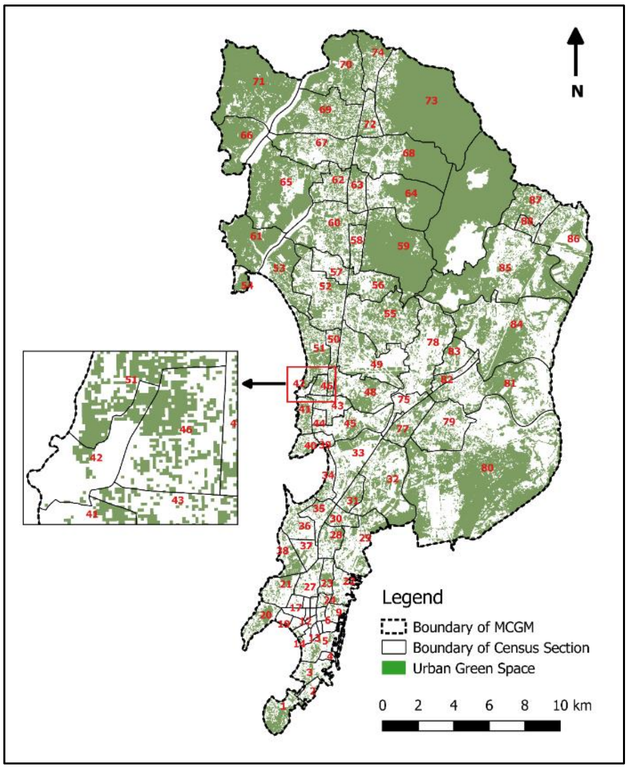

Fig. 5. Map of UGS in Mumbai extracted from satellite images of 30m spatial resolution.

4.2 Association between Spatial Metrics of UGS and SES

4.2.1 At 5m Spatial Resolution: Table 5 gives the results of the ordered logistic regression associating SES with the three spatial metrics computed at 5m spatial resolution. From the results, it is observed that all three spatial metrics show a significant likelihood of association with the SES clusters. However, as suggested by the odds ratio associated with each spatial metric, only FRAC_AM (OR=79204.081 95%CI 45.83-2.322E+08) and nLSI (OR=1350.07 95%CI

7.26-5.109E+05) predicted well the odds of a CS belonging to a higher SES cluster. Thus, an increase of 0.01 unit in the FRAC_AM of a CS, keeping the values of other metrics constant, increased the odds of that CS belonging to a higher SES cluster by 11.94%; similarly, an increase of 0.01 unit in the nLSI of a CS, keeping the values of other metrics constant, increased the odds of that CS belonging to a higher SES cluster by 7.47%. These results imply that the shape complexity and aggregation of UGS in a CS predicted its SES better, vis-à-vis their density. The predicted probabilities of the association between SES and the two spatial metrics, FRAC_AM and nLSI, is shown in Figure 6. It is observed from Figure 6a that for lower values of FRAC_AM, a CS had almost the same probability of association with all the SES categories, and as the value increased, the probability of LS appeared to be the highest. However, at around a FRAC_AM value of 1.27, the probabilities associated with lower SES started falling while those for higher SES started rising sharply. For values of FRAC_AM above 1.40, the probabilities associated with MS, HS, and VHS were high, suggesting that CS enjoying a higher SES tended to have UGS patches of more complex shapes. Figure 6b shows that for lower values of nLSI, the probabilities were higher for LS and VLS; on the other side of the spectrum, for higher values of nLSI, the probabilities were higher for VHS and HS. The curves for lower and higher SES appeared to be inflecting at an nLSI value of 0.45. These results suggest that CS with a lower SES tended to have more aggregated UGS patches while those with a higher SES tended to have more disaggregated UGS patches.

4.2.2 At 15m Spatial Resolution: Table 6 gives the results of the ordered logistic regression associating SES with the three spatial metrics computed at 15m spatial resolution. The results show that only PD and FRAC_AM exhibit a significant likelihood of association to the SES clusters. However, as suggested by the odds ratio associated with the two spatial metrics, only PD (OR=1.019 95%CI 1.004-1.034) predicted well the odds of a CS belonging to a higher SES. An increase of 1 unit in the PD of a CS, keeping the values of other metrics constant, increased the odds of that CS belonging to a higher SES cluster by 1.9%. These results implies that, at 15m spatial resolution, density of UGS patches in a CS predicted its SES better vis-à-vis aggregation and shape complexity of those patches. The predicted probabilities of the association between SES and PD is shown in Figure 7. It is observed that low values of PD of UGS were associated with high probabilities of LS and VLS. As the value of PD increased, the probabilities associated with higher SES categories also began to rise. At higher values of PD, the probabilities associated with VHS and HS were the highest, suggesting that CS with a higher SES tended to have more UGS patches.

4.2.3 At 30m Spatial Resolution: Table 7 gives the results of the ordered logistic regression associating SES with the three spatial metrics computed at 30m spatial resolution. The results show that only FRAC_AM and nLSI exhibit a significant likelihood of association to the SES clusters. As suggested by the odds ratio associated with the two spatial metrics, both FRAC_AM (OR=442.5 95%CI 2.321-128865.15) and nLSI (OR=236.636 95%CI 10.07-7583.258) predicted well the odds of a CS belonging to a higher SES cluster. Thus, an increase of 0.01 unit in the FRAC_AM of a CS, keeping the values of other metrics constant, increased the odds of that CS belonging to a higher SES cluster by 6.3%; similarly, an increase of 0.01 unit in the nLSI of a CS, keeping the values of other metrics constant, increased the odds of that CS belonging to a higher SES cluster by 5.6%. These results imply that the shape complexity and aggregation of UGS in a CS predicted its SES better, vis-à-vis density. The predicted probabilities of the association between SES and the two spatial metrics, FRAC_AM and nLSI, is shown in Figure 8. It is observed from Figure 8a that for lower values of FRAC_AM, the probability associated with VLS was the highest. However, in the FRAC_AM value range of 1.05 to 1.31, the probability associated with LS appeared to be the highest. For values of FRAC_AM approximately above 1.32, the probabilities associated with MS, HS, and VHS were high, suggesting that CS with a higher SES tended to have UGS patches of more complex shapes. Figure 8b shows that for lower values of nLSI, the probabilities were higher for VLS and VLS; on the other side of the spectrum, for higher values of nLSI, the probabilities were higher for VHS and HS. The curves for lower and higher SES appeared to be inflecting at an nLSI value close to 0.6. These results suggest that CS with a lower SES tended to have more aggregated UGS patches while those with a higher SES tended to have more disaggregated UGS patches.

Based on the above results, it is observed that the relative importance of each SM with respect to predicting the SES of a CS varies with spatial resolution at which the UGS are mapped. For example, at 5m and 30m, the results show that FRAC_AM and nLSI are significantly associated with SES clusters, while at 15m resolution PD is the only significant SM associated with SES. Comparing the apparently similar results of 5m and 30m resolutions, it can be observed that the significance of FRAC_AM in predicting the SES has decreased considerably. The reason for this is the earlier mentioned fact that at larger window sizes, the UGS patches appear to have smoother edges, thereby making the patches appear in relatively simpler shapes. The significant variation in the results of each spatial resolution signify that the relationship between the SES of a CS in Mumbai and the SM of the UGS in that CS is indeed susceptible to the effects of changing scales, particularly changing resolutions. Hence, it is imperative that the relationship identified between these remote sensing-based SM and the SES is taken in the context of the spatial resolution of the data used.

Table 5. Ordered Logistic Regression Model for SES and the spatial metrics computed at 5m spatial resolution.

Variable	Value	p	Odds ratio (OR)	OR Lower bound (95%)	OR Upper bound (95%)
Coefficients					
PD	0.005	0.055*	1.005	0.99	1.01
FRAC_AM	11.280	0.004***	79204.08	45.83	2.322E+08
nLSI	7.208	0.008***	1350.07	7.26	5.109E+05
Intercepts					
VLS | LS	14.74	0.01			
LS | MS	16.37	0.00			
MS | HS	17.48	0.00			
HS | VHS	18.58	0.00			

*Significant at $p < 0.1$ Residual Deviance: 261.9635
***Significant at $p < 0.01$ AIC: 275.9635

Table 6. Ordered Logistic Regression Model for SES and the spatial metrics computed at 15m spatial resolution.

Variable	Value	p	Odds ratio (OR)	OR Lower bound (95%)	OR Upper bound (95%)
Coefficients					
PD	0.018	0.014**	1.019	1.004	1.034
FRAC_AM	4.322	0.066*	75.364	0.811	8417.935
Intercepts					
VLS | LS	4.57	0.12			
LS | MS	6.15	0.04			
MS | HS	7.19	0.02			
HS | VHS	8.28	0.00			

*Significant at $p < 0.1$ Residual Deviance: 262.9786
**Significant at $p < 0.05$ AIC: 274.9786

Table 7. Ordered Logistic Regression Model for SES and the spatial metrics computed at 30m spatial resolution.

Variable	Value	p	Odds ratio (OR)	OR Lower bound (95%)	OR Upper bound (95%)
Coefficients					
FRAC_AM	6.092	0.027**	442.500	2.321	128865.15
nLSI	5.467	0.001***	236.636	10.070	7583.258
Intercepts					
VLS | LS	7.2	0.04			
LS | MS	8.9	0.01			
MS | HS	9.9	0.00			
HS | VHS	11.0	0.00			

**Significant at $p < 0.05$ Residual Deviance: 249.2137
***Significant at $p < 0.01$ AIC: 261.2137

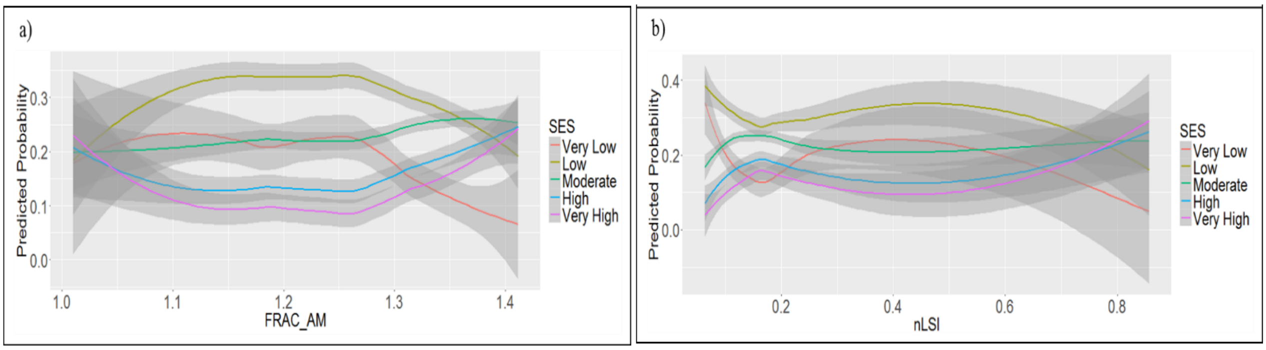

Fig. 6. Predicted probabilities of occurrences of SES clusters against FRAC_AM (a) and nLSI (b) at 5m resolution.

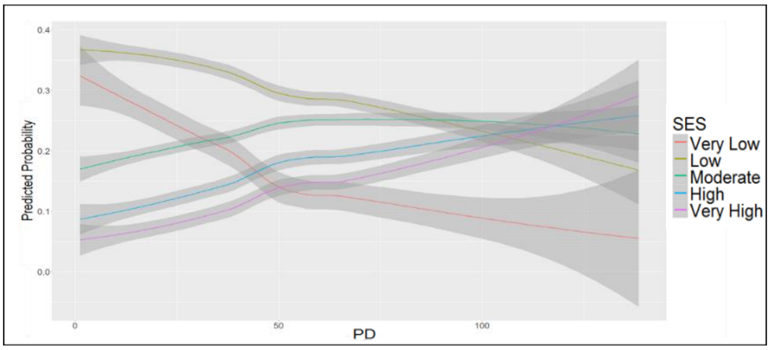

Fig. 7. Predicted probabilities of occurrences of SES clusters across the range of PD computed at 15m resolution.

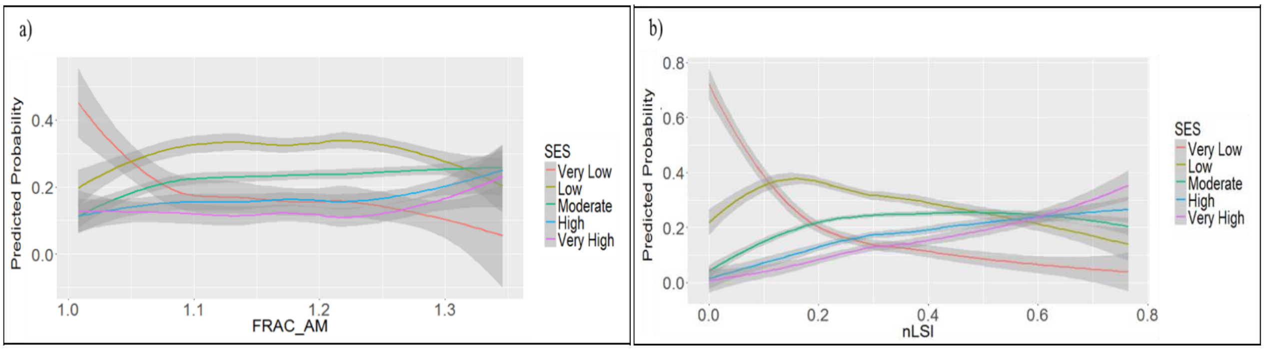

Fig. 8. Predicted probabilities of occurrences of SES clusters against FRAC_AM (a) and nLSI (b) at 30m resolution.

5. CONCLUSION

This work is intended to build on the study presented in Sathyakumar *et al* (2017) wherein the capability of remote sensing-based SM of the UGS in the CS of Mumbai in predicting the socio-economic status (SES) of CS was tested. As spatial metrics, like other spatial data, are prone to the scale effects of the MAUP, it was necessary to analyse the impact of the spatial resolution of the satellite images used on the relationship identified between the SM of UGS and the SES. Hence, the said study was expanded for multiple resolutions, viz. 15m and 30m. The results show that though the remote sensing-based SM can significantly predict the SES, their relative importance varies with the resolution; at 5m and 30m resolutions, FRAC_AM and nLSI are significant, while at 15m, only PD is significant. Thus, it is demonstrated that the relationship identified is indeed susceptible to the effects of changing resolutions, and that it should always be addressed in the context of the spatial resolution used.

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