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Green to gray: Silicon Valley of India

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ABSTRACT

Rapid growth, population concentration and the expansion of urban areas towards peri-urban regions have led to changes in urban structure and composition, and consequently changes in urban ecology. The purpose of this study is to estimate trees in the urban environment through quantification of vegetation cover using multi resolution spatial data supplemented with tree data acquired from field using pre-calibrated GPS. Optimal resolution for extracting trees was attained through fusion of multi resolution (spectral and spatial) data. Results highlight region with spatial extent of 741 sq. km with 9.5 million human population has about 1.48 million trees. Further, urban growth increment is expected to cover 95% of the landscape with paved surfaces by 2020 decreasing vegetation cover while severely affecting the local ecology and environment in addition to human survival.

1. Introduction

Urbanization is an irreversible physical process involving large-scale structural changes in the landscape with an increase in built-up and population densities, thereby affecting the region's ecology and environment. This process has gained momentum during the last two decades due to globalization with opening up markets leading to the accelerated economic activities (Bharath and Ramachandra, 2016; Ramachandra et al., 2013). Cities in India are urbanising at an unprecedented and irreversible rate, as the global proportion of urban population has increased from 28.3% in 1950 to 50% in 2010 (Gerland et al., 2014). As population and its activities increase in a region, the boundary of the city expands to accommodate growth along the urban fringes, leading to urban sprawl with the fragmented urban morphology, thereby impacting local ecology at peri-urban areas and city outskirts (Ramachandra et al., 2012a,b). Landscapes covered with tree cover provide diverse services ranging from micro climate moderation, sequestering carbon (emitted in urban environment), groundwater recharge, etc. while maintaining the natural balance (Parker, 1995). Unplanned urbanization in recent times has fueled the sprawl with lack of adequate infrastructure and basic amenities, necessitating holistic integrated governance approaches for sustainable management of natural resources (Ramachandra et al., 2015). Bangalore the Silicon Valley of India, has witnessed 1005% increase in paved surfaces with 88% decline in green spaces and 79% of water spread regions (Ramachandra and Bharath, 2016). Bangalore known as garden city in seventies would have about 6 percent of green spaces by 2020 (Bharath et al., 2014). Inventorying, mapping and monitoring of trees would help in green initiatives to meet the basic human needs.

Availability of multi resolution spatial data acquired synoptically through space borne sensors help in inventorying, mapping and monitoring of natural resources cost effective way (Gougeon and Leckie, 2006; Ward and Johnson, 2007; Konijnendijk, 2003; McHale et al., 2009; Hirschmugl et al., 2007). The temporal spatial data help in the understanding of urban growth pattern, urbanization rate, and the underlying problems of urban sprawl, etc. These, ultimately, aid in better administration through the provision of basic amenities. Urban sprawl has been characterized considering indicators such as growth, social conditions, aesthetics, decentralization factor, accessibility conditions, density, open space availabilities, dynamics, costs, and social benefits (Ramachandra et al., 2012a,b; Vishwanath et al., 2015). Advances in geo-informatics has aided in optimal exploitation of remote sensing data for inventorying and mapping of natural resources and also extraction of features such as trees, buildings, etc. (Preto, 1992; Ramachandra et al., 2012a,b, 2015; Bharath and Ramachandra, 2016).

Improved spatial, spectral and radiometric resolutions of spatial data with collateral data (collected from field) aid in generating a

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range of spatial statistics of feature attributes such as structure, crown, etc., which will help in the location specific interventions. Most of the optical data obtained through space borne sensors have either higher spatial resolution or spectral resolution but not both due to various limiting capabilities (Kumar et al., 2012) including cost. These can be overcome by using image fusion or pan sharpening (Ramachandra et al., 2011; Choi, 2006; Alparone et al., 2007; Chen et al., 2011) by integrating better spatial information from panchromatic and spectral information from multi-spectral (MS) data (Kumar et al., 2009). Techniques such as intensity hue saturation (Choi, 2006), Principle component analysis (González-Audícana et al., 2004), ICA-independent component analysis (Petrović and Xydeas, 2004; Chen et al., 2011; Dong et al., 2013) have helped in obtaining optimal information through fusion of multi resolution spatial data. PCA was useful in retaining spectral information, while ICA was able to retain high spatial resolution. Recent developments such as Hyper spectra color space resolution merge, MIHS, Wavelet transformations help in attaining detailed accurate information (Nikolakopoulos, 2008).

1.1. Hyperspectra color space resolution merge

Considers an image with ‘n’ input bands and a single pan band to fuse in ‘n-1’ angles of Hypersphere (Padwick et al., 2010). The square of mean and standard deviation of multispectral intensity and panchromatic intensity is calculated as shown in (1)

$$I^2 = \sum_{i=1}^{N} x_i^2, \quad P^2 = (PAN)^2 \tag{1}$$

Then, the forward color transform is done from the native color space to hypersphere color space using mean and standard deviation as per Padwick et al. (2010). Later, intensity match of transformed P^2 and I^2 is done. Further sharpening is done by considering the square root of P^2 to obtain $I_{adj.}$ The intensity component is reverse transformed from HCS to native space using hyperspectral color transform (Padwick et al., 2010).

1.2. High pass filter fusion

Pixel sizes (cell sizes) are extracted as input information. The ratio between the cell sizes of the multispectral data and high spatial resolution data is computed and a high-resolution data is filtered through a high pass convolution filter of size relative to input pixel sizes. The low spatial resolution data is resampled comparable to the high-resolution data based on four nearest neighbors. The HPF image is weighted relative to the global standard deviation of the multispectral bands as per equation (2).

$$\mathrm{W} = (\mathrm{SD(MS)}/\mathrm{SD(HPF)} \times \mathrm{M}) \tag{2}$$

Where:

W = weighting multiplier for HPF image value, SD(MS) = standard deviation (SD) of the MS band to which the HPF image is being added, SD(HPF) = standard deviation (SD) of the HPF image, M = modulating factor to determine the crispness of the output image.

Further each pixel value is calculated using equation (3).

$$\mathrm{Pixel\ (out)} = [\mathrm{Pixel\ (in)}] + [\mathrm{HPF} \times \mathrm{W}] \tag{3}$$

Non-linear absolute histogram equalization is performed to match the data type and range of input data.

1.3. Modified intensity hue saturation fusion

The modified IHS method helps in fusing spatial data differing in spectral responses by assessing the spectral overlap between each Multi Spectral band and the high-resolution PAN band and weighting the merge based on these relative wavelengths (Siddiqui, 2003; Yakhdani and Azizi, 2010).

1.4. Wavelet fusion

Wavelet method based on breaking down of wavelengths of the spectrum into wavelets or packets of discrete reflectance was used to merge the high-resolution image into the intensity values. The wavelet transform provides a framework to decompose images into a number of new images, each one of them with a different degree of resolution (Nikolakopoulos, 2008). Scaling functions were derived from Bi-orthogonal spline column wavelets. The fourth order shift invariant decomposition transform and fourth order reconstruction spline are as per King and Wang (2001). Panchromatic image is decomposed into four images. The first image was replaced with intensity image and an inverse discrete wave transform was performed considering other three decomposed images. This provides a sharper image which is then transformed back to RGB.

Extraction of tree cover: Tree cover extraction algorithms were developed considering that vegetation center is radiometrically brighter than the edge. Methods of optimal match of predefined shapes with local radiometric values were proposed by Larsen (1998). Brandtberg (1999) used edge segments and neighbors with region growing for extraction. Further, Walsworth and King (1999), developed and compared two vegetation delineation techniques involving radiometric surface aspect and other with high pass filter for temporal analysis.

This work considers minima and maxima of local radiometric value based on ground measurements of maximum and minimum tree crown size, girth with predefined edges. Based on the training data collected from the field trees were extracted using matching radiometric quality and range.

2. Study area

Bangalore capital, of Karnataka State, India is geographically located at the south eastern part of Karnataka state. The Greater Bangalore (Fig. 1) city is subdivided 8 zones with 198 wards under the jurisdiction of BBMP. Bangalore is geographically extending from 12°49′5″ N to 13°8′32″ N latitude and 77°27′29″ E to 77°47′2″ E in longitude encompassing an area of 741 km^2. Spatial extent of Bangalore has increased over 10 times between 1949 (69 km^2) to 2006 (741 km^2) and is the 5th largest metropolis in India (Ramachandra et al., 2012a,b; Sudhira et al., 2007) The population of Bangalore urban (BBMP limits) has increased by 48% i.e., from 5.84millon in 2001(Census, 2001) to 8.64 million (Census, 2011) in 2011. The population density in the region has increased from 7881 persons/km^2 (2001) to 11 664 persons/km^2 (2011).

The topography (Fig. 1b) of the region is undulating, the altitude varies from about 740 m to over 960 m above mean sea in the region is main cause for formation of large number of drainages and storage tanks which are responsible for the local rains and cooler climate in summer. Temperature varies from 22 °C to 38 °C during summer and 14 °C–27 °C in winter. Bangalore receives an annual average rainfall more than 800 mm.

Since Bangalore is located on a ridge with natural water courses along the three directions of the Vrishabhavaty, Koramangala-Challaghatta (K&C) and Hebbal-Nagavara valley systems. The drainage allows the flows to cauvery through its tributaries

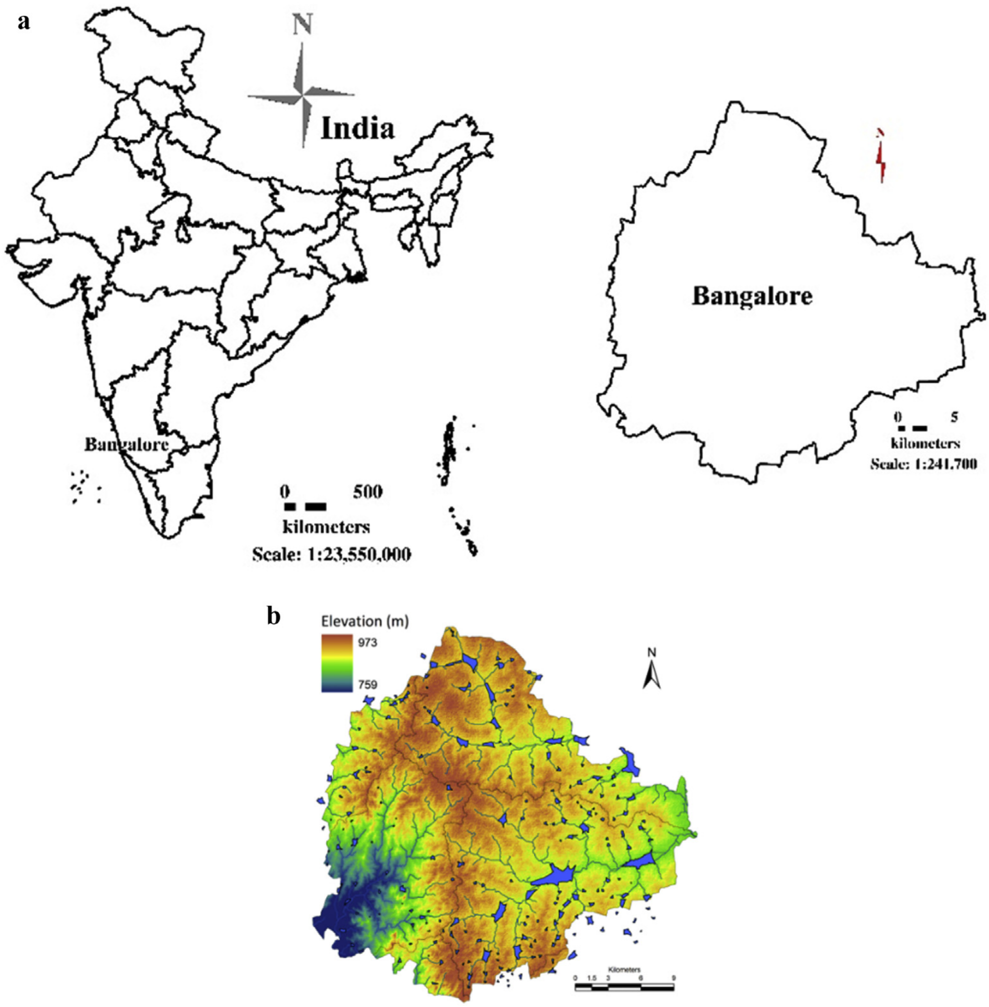

Fig. 1. a: Study area analyzed: Greater Bangalore – Silicon city of India. b: Bangalore's undulating terrain with interconnected lakes. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Arkavathi (East flowing), Pinakini/Pennar (East Flowing) and Shimsha (West Flowing). The central, northern and eastern portion is undulating with the upland tracts occupied by scrubs, while the low lands occupied by series of tanks formed by embanking the streams along the valley for irrigation purposes. These valleys vary in size from small ponds to large lakes. The southern portion of the land consists of hills that are close together and are surrounded by scrub jungles and forests. Geologically the area consists of Granitic and Gneisses rocks in large scale (Bangalore District Gazetteer, 1981; Sekhar and Kumar, 2009), and other rocks include dykes, dolerites, schist's.

Data: Indian remote sensing (IRS) data were used in the analysis, the remote data was supplemented with datasets such as Survey of India topographic sheets of 1:250, 000 and 1: 50,000 scale, population census data (http://censuskarnataka.gov.in), online spatial data portals - Google earth (http://earth.google.com), Bhuvan (http://bhuvan.nrsc.gov.in) and field data gathered using pre-calibrated GPS (Global Positioning System). Table 1 gives the summary of the data used for the analysis.

Table 1
Data used for the analysis.

Data	Year	Description
IRS Resourcesat 2	2013	Land Use Land Cover Analysis(Resolution 5.8 m)
IRS Cartosat 1	2013	Land Use Land Cover Analysis(Resolution 2.7 m)
SOI Toposheets		1:250,000 and 1: 50,000 toposheets for delineating administrative boundaries, and geometric correction
Bhuvan		Support data for Site data, delineation of trees in selected wards
Field Data		For classification, location and canopy estimate of a tree, tree distribution in select wards, frequency distribution analysis and data validation
Google Earth		Support data for Site data, delineation of trees in selected wards
Census of India	1991, 2001, 2011	Population census data

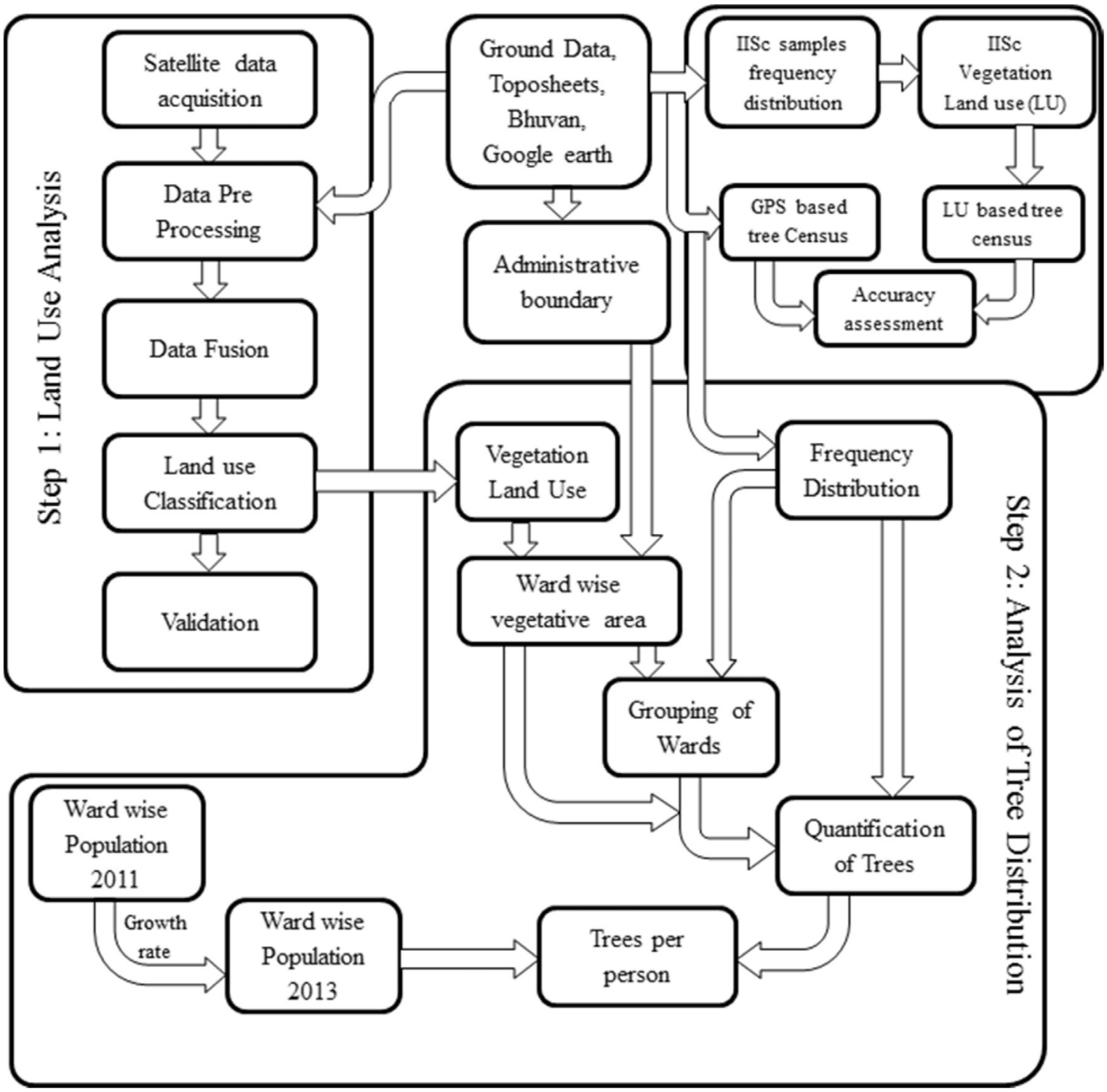

Fig. 2. Method involved in extraction of tree cover of Bangalore.

a) Data Collection: Mapping the spatial extent of species wise tree canopy in select wards using the pre calibrated GPS and through high spatial resolution data including Google Earth.

b) Land use: The spatial extent of vegetation cover was derived from classified remote sensing data. Field data (involving number of trees and spatial extent of tree crown) of sampled wards was compared with the vegetation cover, which helped in getting the number of trees in each ward.

c) Frequency distribution: Based on the field data and virtual online database, sampled wards were grouped into (i) > 500 trees and (ii) < 500 trees. Frequency distribution of number of trees versus average area of tree canopy was analyzed - local maxima, local minima and also edges (with other sub classes)

Knowledge of species wise local maxima and minima aided in understanding probable location ranges with the respective local peak in radiometric brightness (fused data in NIR band). In cases of near neighborhood of a species or group of tree species the maxima and minima is computed based on geometric mean of neighbors at 8 search directions. The choice of which maxima or minima are ultimately considered valid is based on the threshold. These would aid as sampling interval points for extracting pixels from classified land use data.

d) Population projection for 2013: The population for the year 2013 was estimated based on the decadal growth (equation (5))

$$\mathrm{P2013(i) = P2011(i) \times (1 + n \times r(i))} \tag{5}$$

3. Method used

Extraction of trees from multi resolution remote sensing data (outlined in Fig. 2), involved.

(i) Fusion of multi resolution data for optimal spatial and spectral resolutions. Data fusion was performed using various algorithm (such as hyperspectral color space resolution merge, high pass filter fusion, modified intensity hue saturation fusion, wavelet fusion) and performance is evaluated using UIQI index (equation (4)), which helps in measuring the similarity and distortion by considering three factors namely loss of correlation between datasets, radiometric imbalance, and contrast distortion. UIQI index was calculated using,

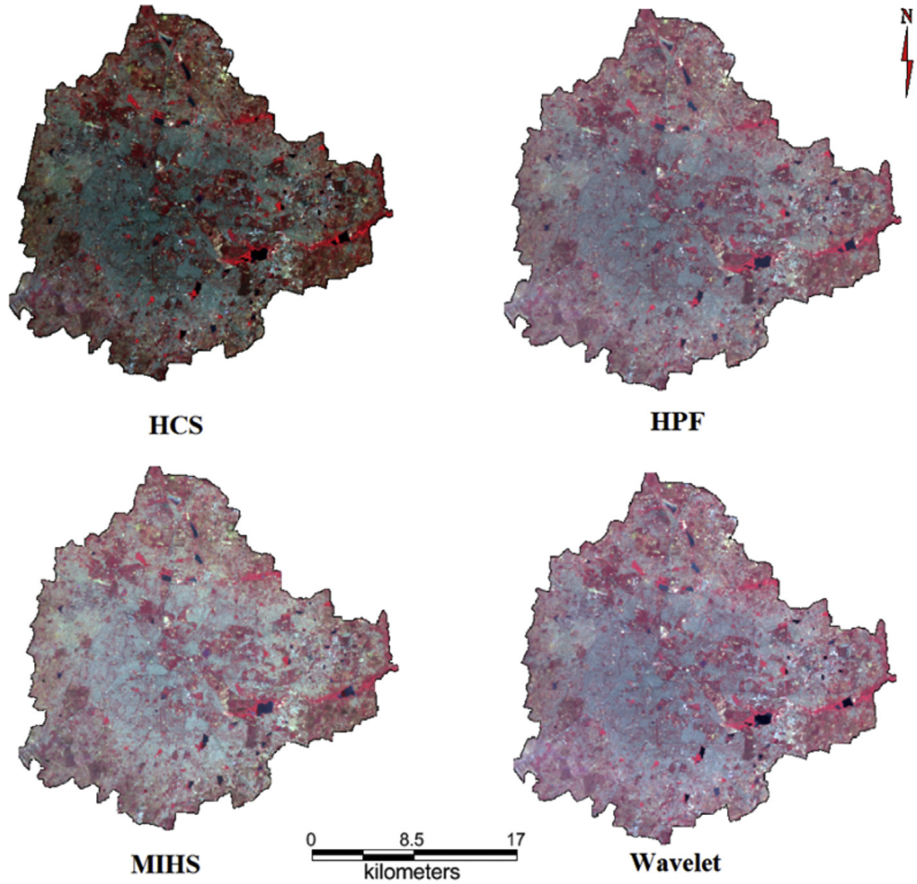

Fig. 3. Results of image fusion carried out to improve the image spectrally and spatially.

Table 2
UIQI – band wise comparison for fused data to understand better fusion method for tree cover analysis.

Fusion techniques	Green	Red	NIR
HCS	1	0.98	0.98
MIHS	1	0.96	0.78
HPF	0.58	0.68	0.91
Wavelet	0.89	0.94	0.98

Table 3
Temporal Land use dynamics of Bangalore from 1973 to 2012.

Class	Urban		Vegetation		Water		Others	
Year	Ha	%	Ha	%	Ha	%	Ha	%
1973	5448	7.97	46,639	68.27	2324	3.4	13,903	20.35
1992	18,650	27.3	31,579	46.22	1790	2.6	16,303	23.86
1999	24,163	35.37	31,272	45.77	1542	2.26	11,346	16.61
2006	29,535	43.23	19,696	28.83	1073	1.57	18,017	26.37
2012	41,570	58.33	16,569	23.25	665	0.93	12,468	17.49

$$\mathrm{UIQI} = Q = \frac{\sigma_{AB}}{\sigma_A \sigma_B} \times \frac{2\mu_A \mu_B}{\mu_A^2 + \mu_B^2} \times \frac{2\sigma_A \sigma_B}{\sigma_A^2 + \sigma_B^2} \tag{4}$$

(ii) land use analyses to understand the land use dynamics – this involved a) spatial data preprocessing (geo rectification using reference data) and generation of False Color Composite (FCC) of remote sensing data (bands – green, red and NIR). FCC helped in locating heterogeneous patches in the landscape, b) selection of training polygons (these correspond to heterogeneous patches in FCC) covering 15% of the study area and uniformly distributed over the entire study area, c) loading these training polygons co-ordinates into pre-calibrated GPS, d) collection of the corresponding attribute data (land use types) for these polygons from the field. GPS helped in locating respective training polygons in the field, e) supplementing this information with Google Earth, f) 60% of the training data has been used for classification, while the balance is used for validation or accuracy assessment. Land use analysis was carried out through supervised pattern classifier - Gaussian maximum likelihood algorithm using fused spatial data. The MLC classifier uses probabilities (Lillesand et al., 2015 to classify each pixel into a particular land use class (categories: Built up; Vegetation; Water; Others). The Gaussian MLC classification technique has been used widely for analysis of land use as this technique is proved to be more superior that other classification techniques (Duda et al., 2000).

(iii) Statistical assessment of classifier performance based on the performance of spectral classification considering reference pixels is done which include computation of kappa (κ) statistics and overall (producer's and user's) accuracies (Ramachandra et al., 2012a,b, 2015; Bharath and Ramachandra, 2016). For earlier time data, training polygon along with attribute details were compiled from the historical published topographic maps, vegetation maps, revenue maps, etc.

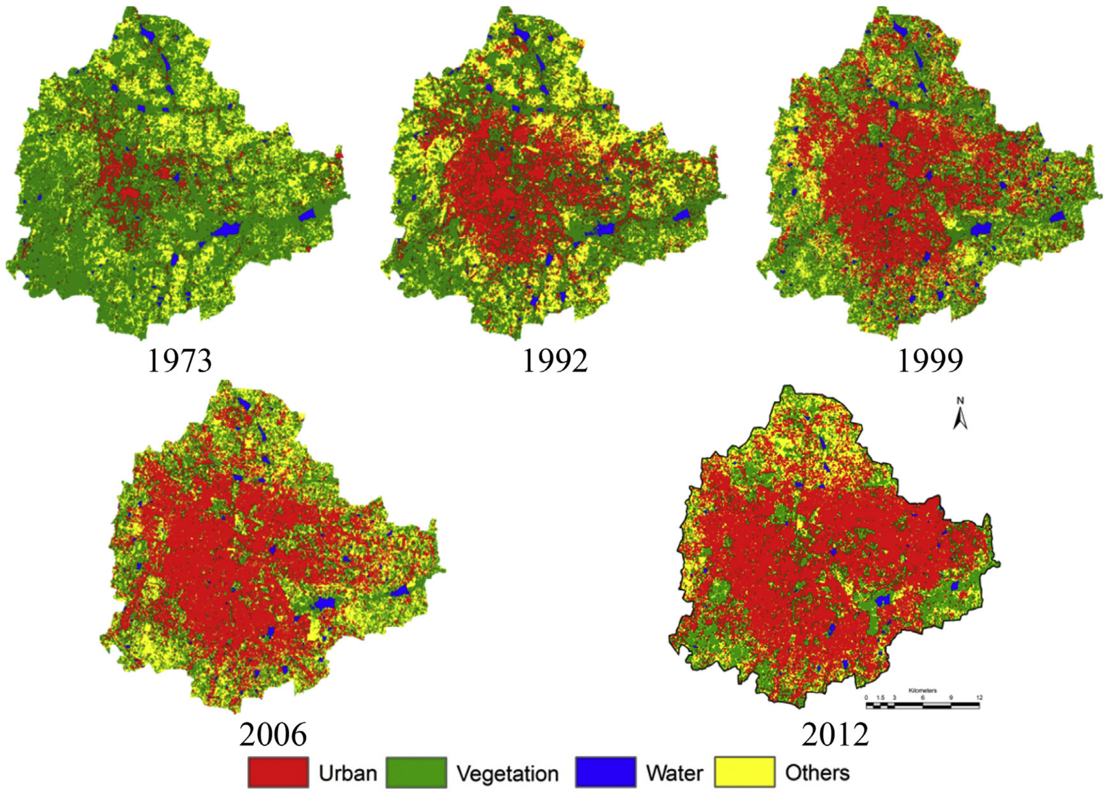

Fig. 4. Land use dynamics of Silicon Valley of India. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

(iv) Field data collection from select wards-mapping of trees using pre calibrated GPS. This involved inventorying, mapping and measurement of tree canopy.

(v) Ward wise trees distribution analyses based on canopy size and spectral analyses of tree canopy (based on species and age). This involved

Where

P2013(i) - Population of ward i for the year 2013.

P2011(i) - Population of ward i for the year 2011.

n - Number of decades = 0.2.

r(i) – Incremental rate of ward i.

The ratio of number of trees in each ward to population in each ward (equation (6)) was determined to quantify tree distribution per person in each ward. Similarly trees per person in Bangalore city is computed (equation (7))

$$\mathrm{TpP(i)} = \frac{\mathrm{Tree(i)}}{\mathrm{P2013(i)}} \tag{6}$$

$$\mathrm{TpP(B)} = \frac{\sum_{i=1}^{198}\mathrm{Tree(i)}}{\sum_{i=1}^{198}\mathrm{P2013(i)}} \tag{7}$$

Where

TpP(i)- Tree per person in ward i.

Tree(i) - Number of trees in ward i.

TpP(B) - Tree per person in Bangalore.

e) ***Validation:*** Validation of tree count for select ward is done by comparing with actual count of trees based on field work (equation (8)).

$$\mathrm{Accuracy} = 100 - (\mathrm{abs}((\mathrm{ClassTree} - \mathrm{GPSTree})/\mathrm{GPSTree}) \times 100) \tag{8}$$

Where

$\mathrm{Class_{Tree}}$ - Tree count based on classified data.

$\mathrm{GPS_{Tree}}$ - Tree count based on field census using GPS.

4. Results and discussions

Fig. 3 presents fused multi resolution data based on HCS, HPF, MIHS and wavelet algorithms and the performance is evaluated through UIQI value (Table 2). All fusion except wavelets were heavy intensive process with 36 h of time on cloud computing networked systems. The results of fusion of multi resolution remote sensing data reveals that HCS performed better among the considered techniques.

Validation with field data apart from the visual evaluation and statistical analysis confirms that HCS performance is better for improving spatial details of MSS images while preserving the spectral properties.

Classification of land use using fused data as vegetation and non-vegetation was performed through Maximum Likelihood classifier. Results indicate the area of vegetation is about 14.08% (100 ha). Validation was performed based on field date collected through various samples. Accuracy assessment and kappa statistics was calculated based on validation image and classified image. Accuracy assessment shows an overall accuracy of 91.5% with kappa of 0.92.

Land use dynamics: Land use dynamics during the last four decades is illustrated in Fig. 5 and category wise land use changes are listed in Table 3. The city witnessed increase in built-up from

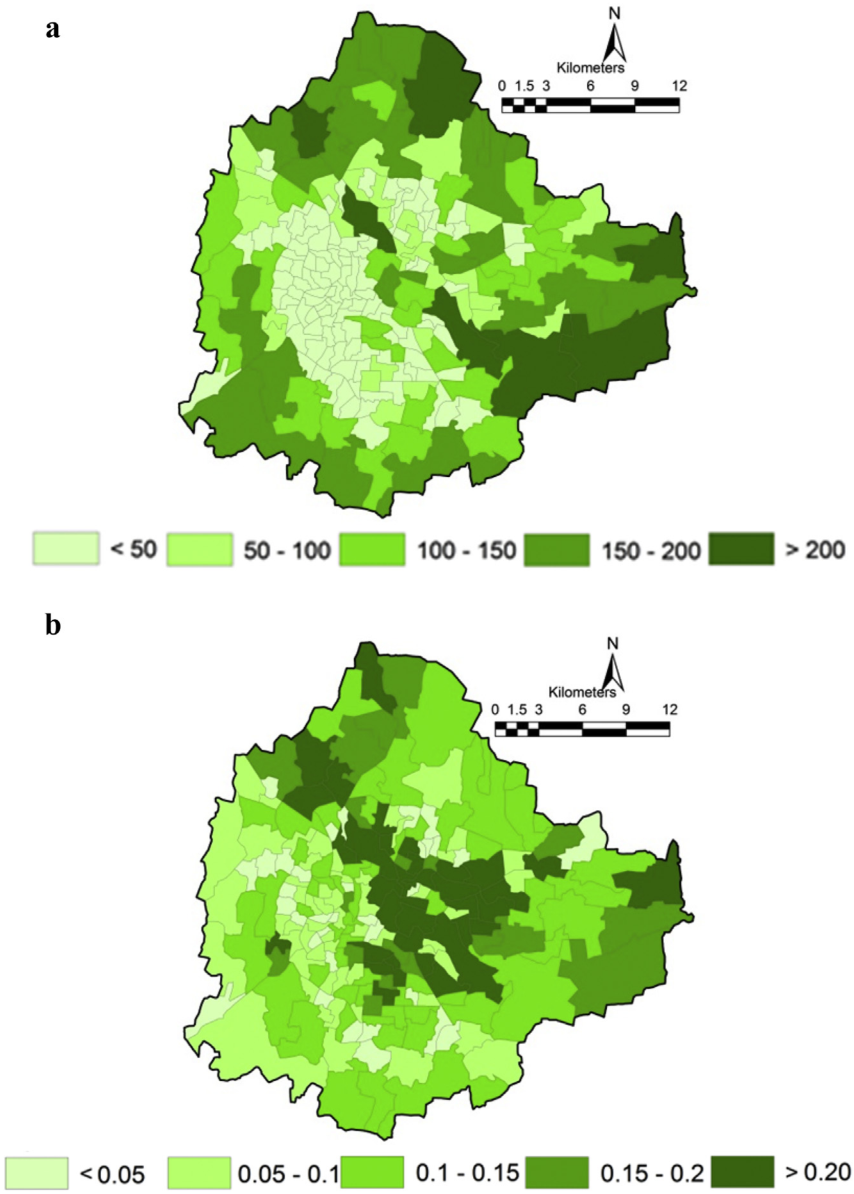

Fig. 5. a: Ward wise vegetation distribution in hectares. b: Ward wise vegetation density.

7.97% (in 1973) to 58.33% in 2012 (Ramachandra et al., 2012a,b; Bharath S et al., 2012). Industrialisation with push in IT and BT sectors witnessed large-scale rapid urbanization during post 90's.

The dense vegetation cover of 68.27% (in 1973) has declined to less than 25% (in 2012). Similar to vegetation, Water bodies have reduced from 3.4% (in 1973) to less than 1% impacting the ground water regime. Other land uses have speckled along the time frame from 20.35% in 1973 to 17.49% in 2012. Analysis of Tree distribution***:*** Vegetation cover in the region was extracted from the classified land use information (Fig. 4). Overlaying administrative boundary of wards, on vegetation distribution aided in assessing ward wise vegetation cover (Fig. 7), which highlights that, minimum vegetation cover (<1 ha) in Chickpete, Shivajinagara, Kempapura agrahara, Padarayanapura, etc., while Varthur, Bellandur and Agaram wards had highest vegetation cover (of >300 ha).

Ward wise vegetation density and distribution is as given in Fig. 5a and b, indicate that Hudi, Aramanenagara and Vasantha pura wards have highest vegetation density (>0.4) compared to Chickpete, Laggere, Hegganahalli, Hongasandra, Padarayanapura (<0.015). The spatial extent of vegetation cover in Bangalore is about 100.20 sq. km with vegetation density of 0.14. Fig. 6 gives the tree distribution in wards based on the field data of location wise tree species and canopy spatial extent. Species wise allometric models of canopy cover (Enquist et al., 2009; West et al., 2009) that specifically helps in predicting species specific intercepts was used to estimate trees in each ward. Based on the canopy size through allometric equations and number of tress mapped of trees.

Wards such as Vathuru, Bellanduru, Agaram, Aramane nagara have >40,000 trees, while Chickpete, Padarayanapura, Shivaji nagara, Kempapura Agrahara, Kushal nagara wards have less than 100 trees. Ward wise aggregation shows that Bangalore city has about 1.478 million trees (Fig. 7a). Validation of tree estimate with field data (collected from select wards) shows an accuracy of 97%. Ward wise tree per person (Fig. 7b), indicates the wards such as Shivaji nagara, Dayananda nagara, Chickpete, Padarayanapura, Kempapura Agrahara has very less number of trees per person (i.e.,

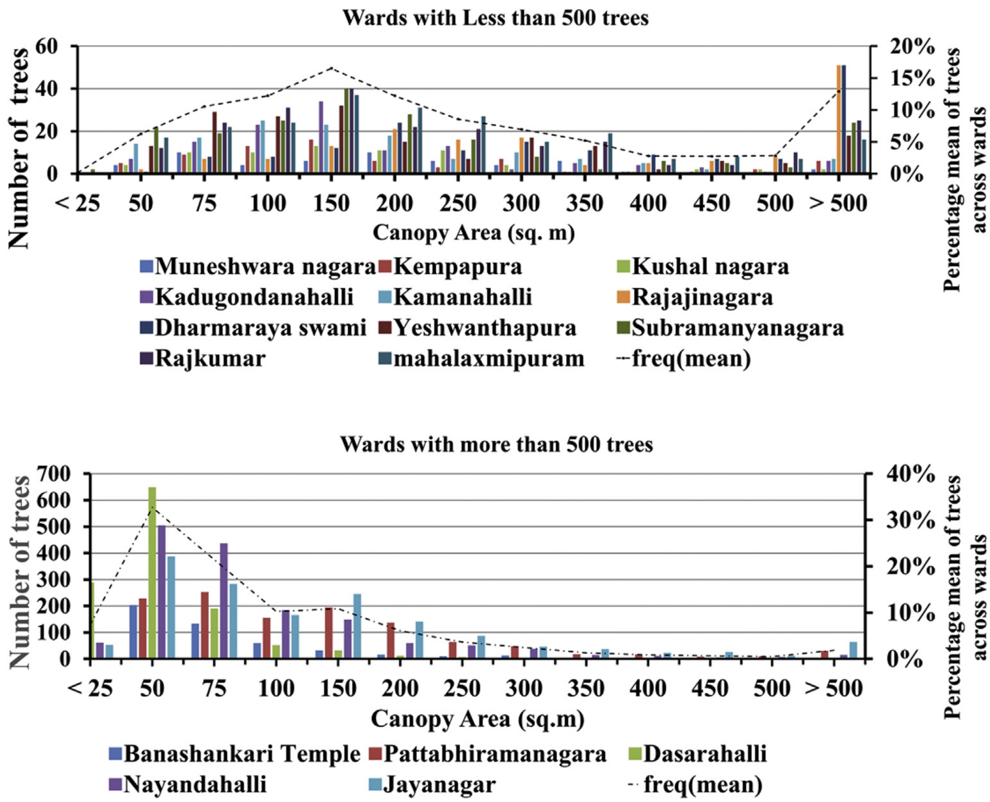

Fig. 6. Tree canopy size distribution based on field measurements in pilot study of various wards.

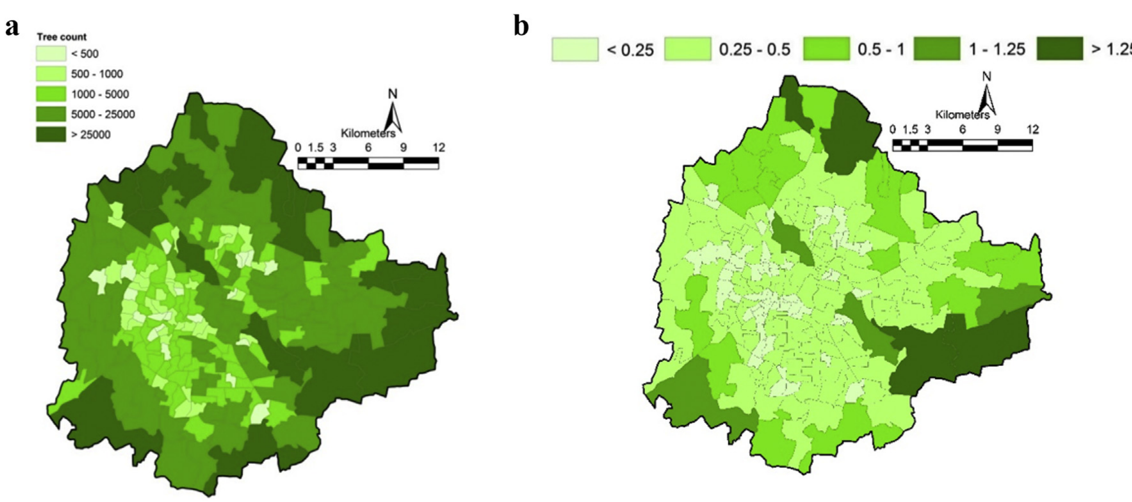

Fig. 7. a: Number of trees quantified in each ward. b: Ratio of trees per person in each wards considered.

less than 1 tree for every 500 persons). Compared to this, Bellanduru, Jakkuru, Varthuru, Agaram, Aramane nagara has 1.25 trees per person. Trees per person details were compiled from literature highlight Gandhinagar city (Gujarat), Nashik city (Maharashtra) has a good number of trees per person i.e., Gandhinagar has 4 trees per person, Nasik 2 trees per person compared to one trees for 7 persons in Bangalore.

5. Conclusion

Analyses of multi resolution remote sensing data reveals that built-up has increased from 7.97% (in 1973) to 58.33% (2012) in Bangalore. The dense vegetation cover of 68.27% (in 1973) has declined to less than 25% (in 2012). The spatial extent of vegetation cover in Bangalore is about 100.20 sq. km with vegetation density of 0.14. Ward wise aggregation shows that Bangalore city has about 1.478 million trees, which is about one tree for every seven persons, which is inadequate even to remove respiratory carbon. Humans on an average respire 540–900 gms of CO_2 per person per day and a hectare of trees sequester about 6–8 ton of CO_2, which indicates that for every person there should have been 8 trees to sequester human respiratory carbon or to have adequate oxygen. This method is useful in tree cover and cannot detect under tree cover in there are specific small trees.

Thus necessitating better technologies intervention in modelling tree cover and analyzing natural resource status and needed intervention to balance the human needs and environmental produce.

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