Fusion of multi resolution remote sensing data for urban sprawl analysis

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Abstract

Urban population is growing at around 2.3 percent per annum in India. This is leading to urbanisation and often fuelling the dispersed development in the outskirts of urban and village centres with impacts such as loss of agricultural land, open space, and ecologically sensitive habitats. This type of upsurge is very much prevalent and persistent in most places, often inferred as sprawl. The direct implication of such urban sprawl is the change in land use and land cover of the region and lack of basic amenities, since planners are unable to visualise this type of growth patterns. This growth is normally left out in all government surveys (even in national population census), as this cannot be grouped under either urban or rural centre. The investigation of patterns of growth is very crucial from regional planning point of view to provide basic amenities in the region. The growth patterns of urban sprawl can be analysed and understood with the availability of temporal multi-sensor, multi-resolution spatial data. In order to optimise these spectral and spatial resolutions, image fusion techniques are required. This aids in integrating a lower spatial resolution multispectral (MSS) image (for example, IKONOS MSS bands of 4m spatial resolution) with a higher spatial resolution panchromatic (PAN) image (IKONOS PAN band of 1m spatial resolution) based on a simple spectral preservation fusion technique - the Smoothing Filter-based Intensity Modulation (SFIM). Spatial details are modulated to a co-registered lower resolution MSS image without altering its spectral properties and contrast by using a ratio between a higher resolution image and its low pass filtered (smoothing filter) image. The visual evaluation and statistical analysis confirms that SFIM is a superior fusion technique for improving spatial detail of MSS images with the preservation of spectral properties.

Keywords: urbanisation, sprawl, resolution, image fusion, SFIM

INTRODUCTION

Urbanisation is the growth in response to many factors - economic, social, political, physical geography of an area, etc. There are two forms of urbanisation i) in the form of townships and ii) unplanned or organic. Many organic towns in India are under the influence of development with new roads, infrastructure improvements, etc. The urban population in India is growing at around 2.3% per annum with the global proportion of urban population increasing from 13% (220 million in 1900) to 49% (3.2 billion, in 2005) and is projected to rise to 60% (4.9 billion) by 2030 (Ramachandra and Kumar, 2008; World Urbanization Prospects, 2005). An increased urban population in response to the growth in urban areas is mainly due to migration. There are 35 urban agglomerations/cities having a population of more than one million in India (in 2001). Urbanisation leads to the dispersed development in the outskirts, which is known as sprawl. The direct implication of such urban sprawl is the change in land use and land cover of the region. These regions are devoid of any infrastructure and normally left out

in all government surveys (even in national population census), as this cannot be grouped under either urban or rural centre. Understanding this kind of growth is very crucial for regional planning to provide basic amenities in those regions. This would help developers and town planners to project growth patterns and facilitate various infrastructure facilities. It is imperative for planning and governance to facilitate, augment and service the requisite infrastructure over time systematically, which requires an understanding of landscape characterisation. Mapping landscapes on temporal scale provide an opportunity to monitor the changes, which is important for natural resource management and sustainable planning activities. Integration of remote sensing data with ancillary information from various other data sources (population, natural resources, etc.) help to arrive at appropriate decision for good governance. Multi resolution, temporal remote sensing data aid in capturing this dynamics.

Fusion of data from multiple sensors aids in delineating objects with comprehensive information due to the integration of spatial information present in the high resolution (HR) panchromatic (PAN) image and spectral information present in the low resolution (LR) Multispectral (MS) images. Remote sensing satellites, such as QuickBird, IKONOS, IRS, bundle a 1:4 ratio of a HR PAN band and LR MS bands in order to support both spectral and best spatial resolutions while minimising on-board data handling needs. Image fusion techniques integrate both PAN and MSS and can be performed at pixel (Cheng et al., 1995), feature (Mangolini, 1994) and decision (Shen, 1990) levels.

The objective of this work is to optimise multi-resolution data analysis to understand landscape dynamics in Greater Bangalore by image fusion and classification. Fusion permits identification of objects on the Earth's surface, especially useful in urban areas because the characteristic of urban objects are determined not only by their spectra but also by their structure. Thus, remote sensing image fusion techniques are useful to integrate a lower spatial resolution MSS image with a higher spatial resolution PAN image.

STUDY AREA AND DATA

Greater Bangalore (figure 1) is the administrative cultural, commercial, industrial, and knowledge capital of the state of Karnataka with an area of 741 sq. km. and lies between the latitudes 12°39'00'' to 13°13'00'' N and longitude 77°22'00'' to 77°52'00'' E. Bangalore city administrative jurisdiction was widened in 2006 by merging the existing area of Bangalore city spatial limits with 8 neighbouring Urban Local Bodies (ULBs) and 111 Villages of Bangalore Urban District. Bangalore has grown spatially more than ten times since 1949 (69 square kilometers) and is the fifth largest metropolis in India currently with a population of about 7 million (Ramachandra and Kumar, 2008).

The data used were IKONOS PAN from 525.8 – 928.5 μm at 1 m spatial resolution acquired on February 23, 2004 and 4 m resolution MSS bands in Blue, Green, Red and NIR part of the electromagnetic spectrum, acquired on November 24, 2004. The size of high resolution (HR) PAN and low resolution (LR) MSS images, covering a portion of Bangalore city, India, is 1200 x 1600 and 300 x 400 respectively. The pairs of the images

Fusion of multi resolution remote sensing data for urban sprawl analysis

were geometrically registered and the LR PAN image was upsampled to 1200 x 1600 by nearest neighbour algorithm. The other data used in the study were Landsat MSS bands of 1973, IRS LISS-III of 2006, and Google Earth image (http://earth.google.com).
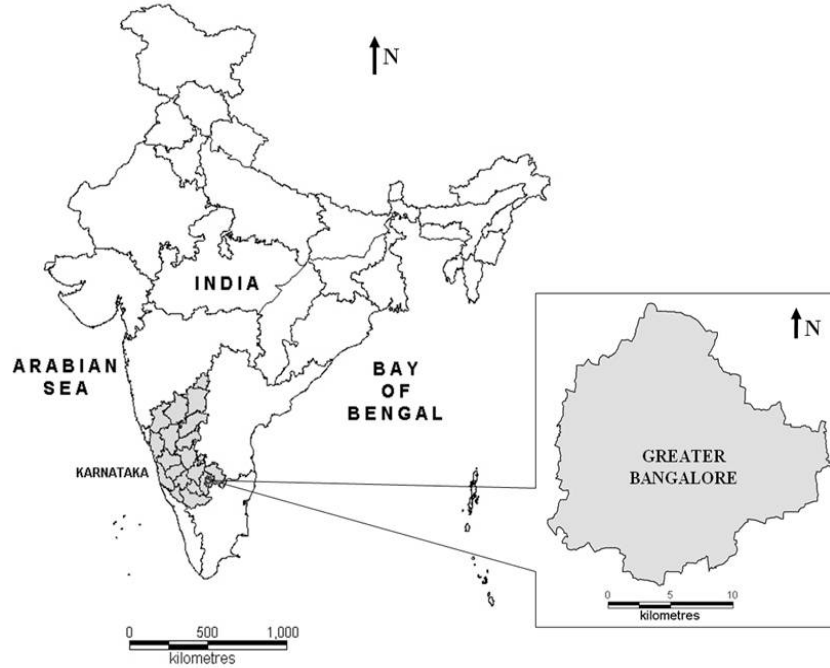
Figure 1: Study area – Greater Bangalore, India.

MODEL

Smoothing Filter-based Intensity Modulation (SFIM) is a general spectral preserve image fusion technique applicable to co-registered multi resolution images (Liu, 2000, Bharath, 2009). SFIM is based on a simplified solar radiation and land surface reflection model (equation 1). Spatial details can be modulated to a co-registered LR MSS band without altering its spectral properties and contrast by using a ratio between a HR image and its low pass (smoothing filter) filtered image.

Digital Number (*DN*) of an optical image in the reflective spectral band (λ) is dependent on irradiance $E(\lambda)$ and the spectral reflectance of the land surface $\rho(\lambda)$, is given by

$$DN(\lambda) = \rho(\lambda)\, E(\lambda). \tag{1}$$

Similarly DN value in a LR image of spectral band λ is represented by $DN(\lambda)_{low}$ and DN value of the corresponding pixel in a HR image of spectral band γ is given by $DN(\gamma)_{high}$. If the two images are taken in similar solar illumination conditions, then

$$DN(\lambda)_{low} = \rho(\lambda)_{low}\, E(\lambda)_{low} \tag{2}$$

$$DN(\gamma)_{high} = \rho(\gamma)_{high}\, E(\gamma)_{high}. \tag{3}$$

Fusion of multi resolution remote sensing data for urban sprawl analysis

SFIM is given by,

$$DN(\lambda)_{sim} = \frac{DN(\lambda)_{low}DN(\gamma)_{high}}{DN(\gamma)_{mean}} \tag{4}$$

$$= \frac{\rho(\lambda)_{low}E(\lambda)_{high}\rho(\gamma)_{high}E(\gamma)_{high}}{\rho(\gamma)_{low}E(\gamma)_{low}} \tag{5}$$

$$= \rho(\lambda)_{low}E(\lambda)_{high} \tag{6}$$

where $DN(\lambda)_{sim}$ is the simulated HR pixel corresponding to $DN(\lambda)_{low}$ and $DN(\gamma)_{mean}$ is the local mean of $DN(\gamma)_{high}$ over a neighbourhood equivalent to the resolution of $DN(\lambda)_{low}$. For a given solar radiation, irradiance upon a land surface is controlled by topography. If the two images are quantified to the same DN range, we can presume $E(\lambda) \approx E(\gamma)$ for any given resolution because both vary with topography in the same way (Liu et al., 1997). We can also presume $\rho(\lambda)_{low} \approx \rho(\gamma)_{high}$ if there is no significant spectral variation within the neighbourhood for calculating $DN(\gamma)$mean. Thus in

$$= \frac{\rho(\lambda)_{low}E(\lambda)_{high}\rho(\gamma)_{high}E(\gamma)_{high}}{\rho(\gamma)_{low}E(\gamma)_{low}} \tag{7}$$

$E(\lambda)_{low}$ and $E(\gamma)_{low}$ cancel each other; $\rho(\gamma)_{low}$ and $\rho(\gamma)_{high}$ also cancel each other; and $E(\gamma)_{high}$ can be replaced by $E(\lambda)_{high}$. We then have a final simple solution of (6). The local mean $DN(\gamma)_{mean}$ is calculated for every pixel of the HR image using a smoothing convolution filter. $DN(\gamma)_{mean}$ is considered as a simulated LR pixel derived from the HR image pixels by spatial smoothing. The image of $DN(\gamma)_{mean}$ is equivalent to the image of $DN(\lambda)_{low}$ in topography and texture because they both have a pixel size of the higher resolution image, and a spatial resolution of the lower resolution image. The final result, the image of $DN(\lambda)_{sim}$, is a product of the topography and texture of higher resolution, $E(\lambda)_{high}$, introduced from the higher resolution image, and the lower resolution spectral reflectance of the original lower image, $\rho(\gamma)_{low}$. It is therefore independent of the spectral property of the HR image used for intensity modulation. As the spectral difference between the lower and the higher resolution images is not fundamental to the operations, equation 6 can be rewritten as:

$$IMAGE_{SFIM} = \frac{IMAGE_{low}IMAGE_{high}}{IMAGE_{mean}} \tag{8}$$

where $IMAGE_{low}$ is a pixel of a LR image co-registered to a HR image of $IMAGE_{high}$, $IMAGE_{mean}$ is a smoothed pixel of $IMAGE_{high}$ using averaging filter over a neighbourhood equivalent to the actual resolution of $IMAGE_{low}$. The ratio between $IMAGE_{high}$ and $IMAGE_{mean}$ in equation (8) cancels the spectral and topographical contrast of the HR image and retains the higher resolution edges only. SFIM is therefore reliable to the spectral properties as well as contrast of the original lower resolution image.

Fusion of multi resolution remote sensing data for urban sprawl analysis

However, for SFIM operations, the lower resolution image must be interpolated to the same pixel size as the higher resolution image by the co-registration process. Also, $IMAGE_{low}$ must have the same pixel size as $IMAGE_{high}$ though with a lower resolution. Otherwise, the spatial information of HR image cannot be fully integrated into the LR image.

ANALYSIS AND RESULTS

The correlation coefficient (CCs) between PAN and the original Green band was 0.44, PAN and Red was 0.47 and PAN and NIR was 0.59. The SFIM result based on the fusion of IKONOS MSS and PAN data is given in Figure 2.
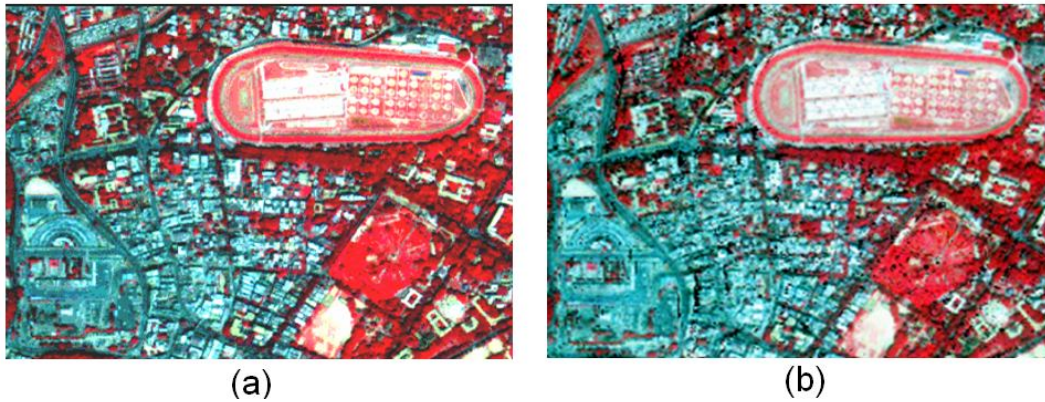

(a)   (b)

Figure 2: FCC of the IKONOS PAN and MSS (a) original bands at 4m, (b) fused bands at 1m.

The performance of the technique was analysed quantitatively by checking the CC that is often used as a similarity metric in image fusion as given in table 1. HIS (Hue-Intensity-Saturation) and BT (Brovey Transform) methods can handle only three bands so G (band 2) – R (band 3) – NIR (band 4) combination was chosen for false colour composite (FCC). CC between original band 2 and 3 and fused bands from Brovey and SFIM is almost equal. However, the CC of the original band 4 (NIR band) and SFIM fused band 4 is higher than Brovey and HIS. Since NIR band is very useful for vegetation and water discrimination and has the highest correlation (0.59) with PAN band, therefore, SFIM is better than the other two methods.

Table 1: CC between original bands and the fused bands from different techniques.

Fusion techniques	Band 2	Band 3	Band 4
HIS	0.22	0.32	0.17
Brovey	0.99	0.98	0.67
SFIM	0.96	0.98	**0.97**

In addition, a universal image quality index (UIQI) (Wang et al., 2005) was used to measure the similarity between two images. UIQI is designed by modeling any image

distortion as a combination of three factors: loss of correlation, radiometric distortion, and contrast distortion given by:

$$Q = \frac{\sigma_{AB}}{\sigma_A \sigma_B} \cdot \frac{2\mu_A \mu_B}{\mu_A^2 + \mu_B^2} \cdot \frac{2\sigma_A \sigma_B}{\sigma_A^2 + \sigma_B^2} \tag{9}$$

The first component is the CC for A (original MSS band) and B (fused MSS band). The second component measures how close the mean gray levels of A and B is, while the third measures the similarity between the contrasts of A and B. The dynamic range is [-1, 1]. If two images are identical, the similarity is maximal and equals 1. This index showed that the SFIM preserves spectral properties even better than Brovey and HIS techniques (Kumar et al., 2009) as given in table 2.

Table 2: UIQI values for the fused bands from different techniques.

Fusion techniques	Original		
	Band 2	**Band 3**	**Band 4**
HIS (Band 2)	0.17	0.27	0.11
Brovey (Band 3)	1.00	0.97	0.63
SFIM (Band 4)	0.97	0.97	0.97

SFIM is more sensitive to image co-registration accuracy. Inaccurate co-registration may result in blurring edges in the fused images. This problem can be resolved using a smoothing filter with a kernel, larger than the resolution ratio between the higher and lower resolution images. The HIS and Brovey transform fusion techniques are not sensitive to the co-registration accuracy as the topographic/textural features are totally replaced by the intensity replacement image. This may not necessarily be an advantage. The SFIM technique is not applicable for fusing images that are fundamentally different in physical properties, such as the fusion between optical images and radar images. SFIM fusion technique aided in integrating a lower spatial resolution MSS image with a higher spatial resolution PAN image. Spatial details were modulated to a co-registered LR MSS image without altering its spectral properties and contrast by using a ratio between a higher resolution image and its low pass filtered image. The visual evaluation and statistical analysis confirms that SFIM is a superior fusion technique for improving spatial detail of MSS images with the preservation of spectral properties.

Figure 3 shows the classified image of 1973 (79 m) and 2006 (23.5 m) obtained with four land use categories (built-up, vegetation, water and open land) for Greater Bangalore. The fused image has retained both the spectral and spatial properties and gives finer details not visible in the two LR classified images. Table 3 gives the details of the classified images.

Table 3: Landuse statistics of Greater Bangalore.

Year ↓	Class →	Built up	Vegetation	Water	Others
1973	**Ha**	5448	46639	2324	13903
	%	**7.97**	**68.27**	**3.40**	**20.35**
2006	**Ha**	29535	19696	1073	18017
	%	**43.23**	**28.83**	**1.57**	**26.37**

Temporal analysis of Greater Bangalore data showed that there has been a 466% increase in built up area from 1973 to 2006 leading to decline of 54% area in water bodies, attributing to intense urbanisation process. The rapid development of urban sprawl has many potentially detrimental effects including the loss of valuable agricultural and eco-sensitive (e.g. wetlands, forests) lands, enhanced energy consumption and greenhouse gas emissions from increasing private vehicle use (Ramachandra and Kumar, 2008).
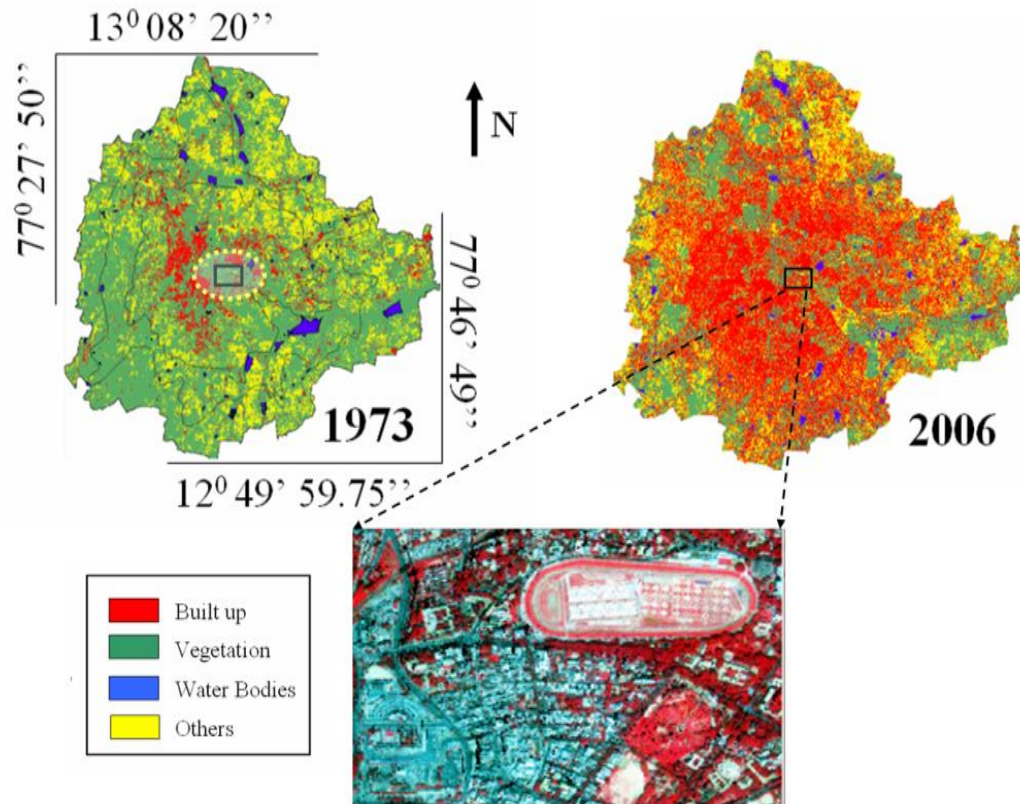

Figure 3: Classified images of 1973 and 2006. **Fused image of area highlighted in rectangular box in the two classified images.**

Vegetation has decreased by 58% from 1973 to 2006. Multi-storied buildings have come up on some lake beds that have totally intervene the natural catchment flow leading to artificial floods (Ramachandra and Kumar, 2008). Urbanisation has also enhanced land surface temperature in urban areas from the circumference ground creating heat island effects.

Fusion of multi resolution remote sensing data for urban sprawl analysis

CONCLUSIONS

The advantage of the SFIM over the HIS and Brovey fusion technique is that it improves spatial details with the fidelity to the image spectral properties and contrast. This technique can be used to perform high speed real-time image fusion process and visualisation. The SFIM technique is not applicable for fusing images that are fundamentally different in illumination conditions or physical properties such as the fusion between optical images and radar images. The case study unravels the pattern of growth in Greater Bangalore and its implication on local climate and also on the natural resources, necessitating appropriate strategies for the sustainable management. This would help developers and town planners to project growth patterns and facilitate various infrastructure facilities. The study reveals the type, extent and nature of sprawl taking place in a region. Methods of change detection from multi-resolution images integrating spectral, structural and textural features to generate change patches in a landscape are future scope of this work.

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Fusion of multi resolution remote sensing data for urban sprawl analysis

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Fusion of multi resolution remote sensing data for urban sprawl analysis