FINAL MANUSCRIPT

Texture-based identification of urban slums in Hyderabad, India using remote sensing data

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A B S T R A C T

This paper outlines a methodology to identify informal settlements out of high resolution satellite imagery using the concept of lacunarity. Principal component analysis and line detection algorithms were applied alternatively to obtain a high resolution binary representation of the city of Hyderabad, India and used to calculate lacunarity values over a 60 × 60 m grid. A number of ground truthing areas were used to classify the resulting datasets and to identify lacunarity ranges which are typical for settlement types that combine high density housing and small dwelling size – features characteristic for urban slums in India. It was discovered that the line detection algorithm is advantageous over principal component analysis in providing suitable binary datasets for lacunarity analysis as it is less sensitive to spectral variability within mosaicked imagery. The resulting slum location map constitutes an efficient tool in identifying particularly overcrowded areas of the city and can be used as a reliable source in vulnerability and resilience assessments at a later stage. The proposed methodology allows for rapid analysis and comparison of multi-temporal data and can be applied on many developing urban agglomerations around the world.

Introduction

The rapid advance of urbanisation throughout the world has caused the first ever prevalence of the number of people living in urban settlements than in rural ones (UN, 2009), an increase of 10% or approximately 500 million people from 1990. This phenomenon essentially marks a new stage in the pace of urban development. Such a high rate of urbanisation is often unaccompanied by adequate development of infrastructure, be it housing, transport or utility grids, particularly in the developing world, where most of the urbanisation takes place. Together with the large share of informal low-paid employment, this process extraordinarily contributes to the growth of informal settlements (UN, 2009).

Generally, urbanisation can lead to both, the growth of informal as well as formal urban settlements, of low-, medium- and potentially upper class housing. 'Slum' has become a term to uniformly refer to the large variety of high-density, vastly developing, lower class residential areas with small dwelling unit sizes found in the cities of the developing world, although no common definition across countries exists and some countries lack a definition at all.

The UN Data Glossary (UN, 2011) attempts a common definition but remains rather broad by defining slums as "areas of older housing that are deteriorating in the sense of their being underserviced, overcrowded and dilapidated", whereas the UN HABITAT (UN, 2006) defines slums as households that "lack any one of the following five elements:

1. durability of housing (permanent and adequate structure in non-hazardous location),
2. sufficient living area (not more than two people sharing the same room),
3. access to improved water (access to sufficient amount of water for family use, at an affordable price, available to household members without being subject to extreme effort),
4. access to improved sanitation (access to an excreta disposal system, either in the form of a private toilet or a public toilet shared with a reasonable number of people),
5. security of tenure (evidence of documentation to prove secure tenure status or de facto or perceived protection from evictions).

Abbreviations: HMDA, Hyderabad Municipal Development Authority; MCH, Municipal Corporation of Hyderabad; HUDA, Hyderabad Urban Development Authority; HUA, Hyderabad Urban Agglomeration; INR, Indian Rupee.

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The UN provides general updates on the issue in its "State of the World's Cities Reports", and UN HABITAT dedicated a whole volume to the challenge of slums in 2003 (UN, 2003). More recent estimates give a slum population of about 16% of the world's population (UN, 2009), with India officially scoring below average with 6% slum population (GoI, 2010b) despite the fact that the UN HABITAT definition is stricter than the one applied in India.

In India, slums can be either formally authorised by the city authority or can sprout informally. The designation of a residential area as a slum comes with a certain degree of security and access to facilities, and is necessary to benefit from additional government services and basic infrastructure in return. Slums normally start as informal settlements and are eventually approved after a long time of informal existence. Following definitions of slum areas are used in India:

1. All specified areas in a town or city notified as 'Slum' by state/local government and UT Administration under any Act including the 'Slum Act'.
2. All areas recognized as 'Slum' by state/local government and UT Administration, Housing and Slum Boards, which may have not been formally notified as slum under any act;
3. A compact area of at least 300 population or about 60–70 households of poorly built congested tenements, in unhygienic environment usually with inadequate infrastructure and lacking in proper sanitary and drinking water facilities (Census of India, 2001).

Slums in India are additionally categorized by their building type, which is described as (semi-) pucca or (semi-) kutcha. Pucca refers to houses of more permanent building materials, such as burned bricks, stones, asbestos cement sheets, (corrugated) metal plates and other roof tiles, whereas kutcha describes the use of non-permanent building materials, for example, clay, wood, bamboo, leaves or carton. Pucca houses can have more than one storey and always show a flat roof, while kutcha houses are one storey only and often resemble tents (Baltsavias & Mason, 1997; The Community Studies Team, 2007).

India aims to be slum-free by 2014 (GoI, 2010a) and in so trying, amongst other initiatives, launched an extensive government scheme of 12.7 billion Indian Rupees (INR) (USD 278 million), the Rajiv Awas Yojana. However, recent forecasts to the socio-economic development of Indian cities uniformly estimate that slums will remain one of India's urban features well into the future (UN, 2009).

For obvious reasons, a slum detection algorithm which is based on satellite imagery alone is not capable of considering such properties of a slum as land tenure or service provision. Nevertheless, since it is generally accepted that housing size and density are distinctive properties of a slum (Niebergall, Loew, & Mauser, 2008), it is appropriate to rely on the internal building structure of a slum in the methodology development process.

Reliable identification of slums and tracking of their growth has always been a difficult task for urban administrators in the developing world. As the alternatively used term 'informal settlement' suggests, such developments are, particularly in the early stages, not necessarily reported to the authorities and therefore lack proper referencing in land property registers or urban development plans. The need to know past and future locations of slums arises from the responsibility of a government to provide for its citizens, which can be narrowed down to the identification of the groups in need, development of housing, employment and service provision policies as well as risk reduction measures. While such information might be available on the lowest levels of India's city structure (colonies and wards), the imperfect vertical communication often leads to situations when municipalities and municipal corporations cannot appropriately describe fine spatial and socio-economical structure of the areas they manage, which is vitally important for adequate steering of the city growth. The reliance on the 1994 slum location data in the 2010 Master Plan for Hyderabad is an eminent indicator of the necessity of our research, which aims to provide local and regional planning authorities with a tool, capable of identifying slums through the use of recent high-resolution satellite imagery. Therefore, new methodologies and tools as well as techniques and policies are required to monitor urban growth and alteration across the megacity and to forecast areas of risk – all within shorter time frames and at a larger scale than previously accepted (Herold, Goldstein, & Clarke, 2003). This will support a more proactive and sustainable urban planning and land management (UN, 2002).

The ascent of increasingly high resolution sensors aboard earth-orbiting civil satellites has created spatiotemporally continuous and politically less biased sources of data about the surface of our planet. While first uses of remote sensing data for land use classification were confined to large-scale cartographic and agricultural studies (Lillesand, 1990), the 1970s also saw the initial use of satellite imagery in urban research (Ellefsen, Swain, & Wray, 1973; Lo & Welch, 1977). Some 40 years later, urban planning and administration in megacities is becoming unthinkable without the use of information derived from remote sensing platforms (Maktav, Erbek, & Jürgens, 2005). For example, the mere land use classification of built-up and non-built-up areas performed during the urban expansion of Greater Dhaka, Bangladesh, has produced important insights into the spatial patterns of the city's expansion (Dewan & Yamaguchi, 2009).

Accurate detection and classification of informal settlements using remote sensing data pose real challenges to researchers and decision-makers alike. Unlike agricultural land or other natural vegetation types, urban structures lack unique and easily distinguishable spectral signatures. Even to a first approximation cities are not spatially uniform bodies but constitute a collection of discrete objects, be it streets, houses or green spaces. This is particularly evident in slums where the variety of materials used for roof construction is so great (Baltsavias & Mason, 1997) that it effectively prohibits any attempt of urban fabric classification based on spectral properties alone. On the other hand, internal spatial characteristics of slums such as housing density, size and structure of individual dwelling units emerge as promising and efficient methods of slum detection.

Baud, Kuffer, Pfeffer, Sliuzas, and Karuppannan (2010) successfully merged local knowledge with an indicator-based visual interpretation technique to extract different classes of residential areas matching administrative settlement categories (formal/informal) using high resolution satellite imagery of Delhi/India. The approach, however, extensively relies on manual image processing and is thus of limited use in operational monitoring circumstances where limited human resources and time frames are available for processing of multitemporal datasets. Nevertheless, visual interpretation is still frequently used for visual checking and evaluation of classification carried out by other means (Hurskainen & Pellikka, 21 October, 2004).

The growing availability of computing power as well as the need to continuously track land use change within large and often nebulous spatial boundaries have created a need for rapid slum identification which does not allow for extensive but time-consuming fieldwork. This is the area where fully automated methods start to play an increasingly important role. While summarising challenges and achievements of object detection using multi-scale satellite imagery, Blaschke (2010) stresses the importance of automated object detection in object-based image analysis as the approach becomes increasingly used in planning and decision-support workflows. Object-based analysis of very high resolution imagery is proven to provide consistently better results than per-pixel classification, particularly in parts of a city characterised by low spectral separability of urban features (Bhaskaran, Paramananda, & Ramnarayan, 2010).

Aiming to identify slums in Hyderabad, we consider cities to be complex systems composed of non-linear and multiple scale iterations of spatial and physical heterogeneous components (Amorim, Filho, & Cruz, 2009). Hence, they can be analysed by the means of fractal mathematics. Several authors (Amorim et al., 2009; Filho & Sobreira, 2008; Myint & Lam, 2005) successfully used lacunarity as a measure of surface texture to classify urban settlements and to detect different housing types within city boundaries. It was Gefen, Meir, Mandelbrot, and Aharony (1983) who defined lacunarity as a measure of the deviation of a geometric object, such as a fractal, from translational invariance, being a suitable indicator to measure spatial heterogeneity. Since lacunarity values represent the distribution of gaps within an image at various scales, it is considered to be a suitable and promising tool, capable of assessing urban structure and isolate distinctive morphological features.

The main focus of this paper is to identify the locations of slums in Hyderabad/India aiming to be useful to urban decision makers. We therefore explore the extent to which remote sensing data and advanced image processing techniques can be applied to identify slums with minimal operator intervention.

Specifically, the following objectives are addressed:

1. Identify slums in Hyderabad/India using very high resolution satellite imagery;
2. Test the methodology of slum identification which is based on the lacunarity algorithm
3. Compare the performance between principal component analysis and line detection algorithms in production of suitable binary datasets for the following lacunarity computation.

Study area

Hyderabad is the capital of Andhra Pradesh state in central South India. It grew from about 1 million inhabitants in 1951 to about 7 million in 2001. It is characterised by growth rates of more than 50% during 1981-91 and of 27% during 1991−2001(GHMC, 2010). The urban agglomeration is expected to host 10-million inhabitants by around 2020, whereas the scenarios for the wider urban area (HUDA area as per MCH, 2005) project a crossing of the 10 million mark by 2015.

Hyderabad is a city that benefited substantially from India's high-tech boom, with the majority of the GDP generated in the information technology, pharmaceutical and chemical industries. Like many other emerging megacities, Hyderabad suffers from significant social inequalities; more than a third of its population is believed to live in slums of various qualities (HMDA, 2010). The latest available data on slum growth is summarized in Table 1:

Table 1
Growth of slums and slum population in Hyderabad.

Year	No. of slums	Slum population, thousands	City population, thousands	% of total population	Annual growth rate
1962	106	120	1233	9.73	
1967	194	168			
1972	282	300	1732	17.32	9.6
1976	300	320			
1978	377	400			
1979	455	408			
1981	470	540	2251	23.99	6.75
1986	662	859			
1994	811	1258	3298	38.14	6.72
2001[a]		601	3454	17.4	
2001[b]	1142	1411	3633	38.83	

(Sources: Hyderabad Concept Plan, MCH and Master Plan for Hyderabad Metropolitan Area by HUDA 2003, as quoted by HMDA (2010); MCH, 2005; Government of India, 2010c).

[a] According to MCH.

[b] According to the Government of India.

The disagreement of official sources on the slum population in 2001 can be possibly explained by use of different slum notification data. The notification process is complicated and sometimes lengthy, in which the community needs to prove certain characteristics listed in the Andhra Pradesh Official Slum Act of 1956 (Naidu, 1990). As the notification is also a political process, the inhabitants of recently formed settlements, particularly poor and dilapidated areas, and former rural migrants often lack the necessary political lobbying.

Given the large proportion of the population of the city living in slums, it is remarkably distressing that the assessment and monitoring of slums in Hyderabad is performed on a rather ad-hoc basis, with results that vary significantly among different government agencies. However, one should not forget that the notification of slums comes with a certain responsibility of the authority to provide for basic services. Therefore, the publication of slum statistics as well as the development of a slum detection algorithm has a certain political notion.

Methodology

Data source

Very high resolution imagery from the QuickBird satellite was used as a source of remote sensing data. The QuickBird sensor collects multispectral and panchromatic imagery concurrently, with resolutions of 2.44−2.88 m and 0.61−0.72 m, respectively, depending upon the off-nadir viewing angle (0−25 degrees) (Cheng, Toutin, & Zhang, 2003). The imagery used in this study was delivered by the data provider as a gridded dataset which was radiometrically calibrated, pan-sharpened, corrected for sensor- and platform-induced distortions and mapped to a UTM projection zone 44N. The data covers 400 km^2 of urban territory within a rectangular bounding box of 78°22′-34′ east longitude and 17°18′-30′ north latitude.

Data preparation

The lacunarity calculation algorithm works best with binary data which is represented as a matrix holding 0 (no housing) and 1 (housing) values (Malhi & Román-Cuesta, 2008). At a sufficiently fine resolution such a matrix is capable of representing the internal structure of slums as a grid of dwelling units and open space between them.

Since there is no universally accepted procedure of obtaining binary datasets for lacunarity calculations out of pan-sharpened satellite imagery, two different binarisation methods were used and compared: PCA- and line detection-based.

Method 1 combined principal component analysis and threshold binarisation. Since urban zones are characterized by generally higher internal variability than the non-urban ones (Weizman & Goldberger, 2009), principal component analysis (PCA) seems to be an appropriate technique which can be used to reduce the dimensionality of the data. A study by Muchoney and Haack (1994) found PCA superior to an unsupervised classification of composite imagery and hence more appropriate for an automated feature detection procedure.

Method 2 is based on the assumption that while the housing structure within informal settlements in India does not normally

Table 2
Results of principal component analysis.

Component	Eigenvalue	Vector	Importance
1	46167.55	−0.5476, −0.6050, −0.5780	99.29%
2	286.40	0.6285, 0.1586, −0.7615	0.62%

follow any regular pattern (Baud et al., 2010), the edges between a dwelling unit and the surrounding area (open space, streets and paths) are still distinguishable. Therefore, it is appropriate to apply a line detection algorithm as implemented in VIPS (Martinez & Cupitt, 2005) and to create a binary matrix suitable for the lacunarity calculation by this method. Both methods are described in more detail hereafter.

Method 1 (PCA-based)

Original multispectral imagery was imported into GRASS GIS, split into red, green and blue colour channels and analysed using the *i.pca* method (Richards & Jia, 2006). The process took approximately 30 h on a laptop computer (peak performance 10 Gflops) and resulted in the distribution of eigenvalues as per Table 2.

The extremely high importance of the first component let us use it as an appropriate unidimensional representation of the RGB colour space of the satellite image. The first component matrix was stretched to a range of 0…255 and then converted into binary matrix using the VIPS binarisation function (Martinez & Cupitt, 2005), setting black/white threshold to 127. This turns pixels having spectral value lower than 127 (exactly in the middle of the value diapason) into white and those higher than 127 into black, respectively, producing the binary matrix *pca_127*. In order to identify the most suitable threshold, binary matrices are created using 120 and 130 as splitting points, producing binary matrices *pca_120* and *pca_130*. Fig. 1 presents a sample result of the binarisation process.

Method 2 (line detection-based)

Original multispectral image was converted into a panchromatic line matrix using the im_lindetect function as defined by Martinez & Cupitt, 2005. In order to produce binary matrices comparable to those used by method 1, different binary threshold values had to be chosen. Those were empirically set at 60, 70 and 80, obtaining binary matrices *line_60*, *line_70* and *line_80* respectively. This method has produced three binary datasets, the extract from one of them is visualised by Fig. 2.

Lacunarity calculation

Lacunarity was computed using the algorithm provided by Malhi and Román-Cuesta (2008), where lacunarity Λ of a subset P is defined as:

$$\Lambda = \sigma_r/\bar{x}_r^2 + 1$$

where σ_r is the variance and $\bar{x}_r$ is the arithmetic mean of the number of filled pixels within all r-sized unique square subsets (referred to as sampling window) of the larger subset P of the original binary image. As the sampling window of size r traverses through P, the number of filled pixels within every position of this window is counted and stored in an array. After all unique sampling window positions are processed the algorithm calculates variance σ and arithmetical mean $\bar{x}$ for P and then computes a single lacunarity value Λ for this subset.

The algorithm produces a rectangular matrix holding decimal lacunarity values, which is stored as a flat GeoTIFF image. Since the georeferencing parameters of the original imagery have been known, it was possible to georeference the lacunarity matrix by producing ESRI world files.

According to Malhi and Román-Cuesta (2008), the floating window should be big enough to cover the largest units of interest (that is a dwelling unit in our case), but do not exceed the size which makes it possible to reveal finer-scale information on variation in the image. As typical dwelling units in slums rarely exceed several metres in any dimension and gaps between houses are expressed in fractions of a metre rather than in whole metres, the size of floating window was kept comparatively small, being set in three runs at 5, 10 and 15 px (3, 6 and 9 m respectively). This takes into account the findings of Niebergall et al. (2008), who stated that high building density and small building size are the most important characteristics for identifying informal settlements from very high resolution image data.

A Python routine was developed to perform the calculations, which took approximately 20 h on a laptop computer (peak performance 10 Gflops) despite the extensive use of Numeric Python and Scientific Python fast computation techniques.

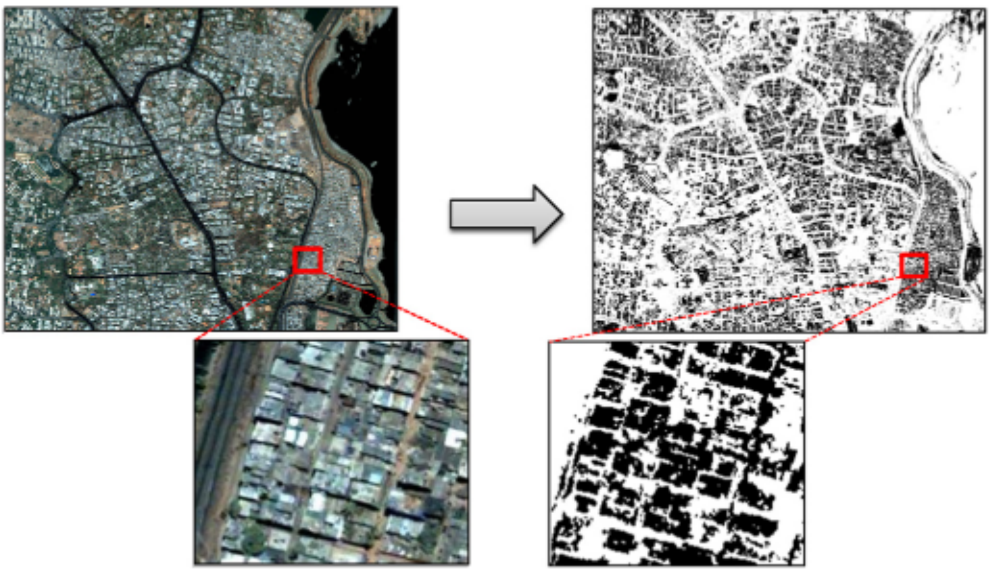

Fig. 1. Sample natural colour image and binary matrix pca_127 (both covering Punjagutta area of Hyderabad). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

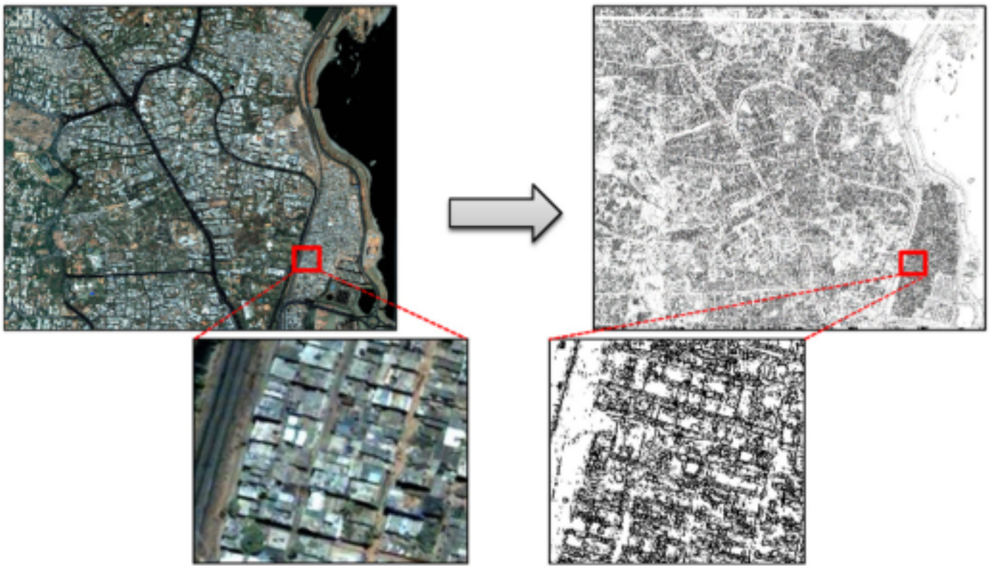

Fig. 2. Sample natural colour image and binary matrix line_70 (both covering Punjagutta area of Hyderabad). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Results

Using three different binarisation thresholds and floating window sizes, both algorithms have produced 18 considerably distinct lacunarity matrices for the whole of Hyderabad (9 each).

To decide which of these parameterisations and choice of the binarisation algorithm yield the best results, these 18 matrices were compared with several subsets of the original satellite image where settlement structure was identified by ground truthing surveys during research stays in Hyderabad in autumn 2009 and winter

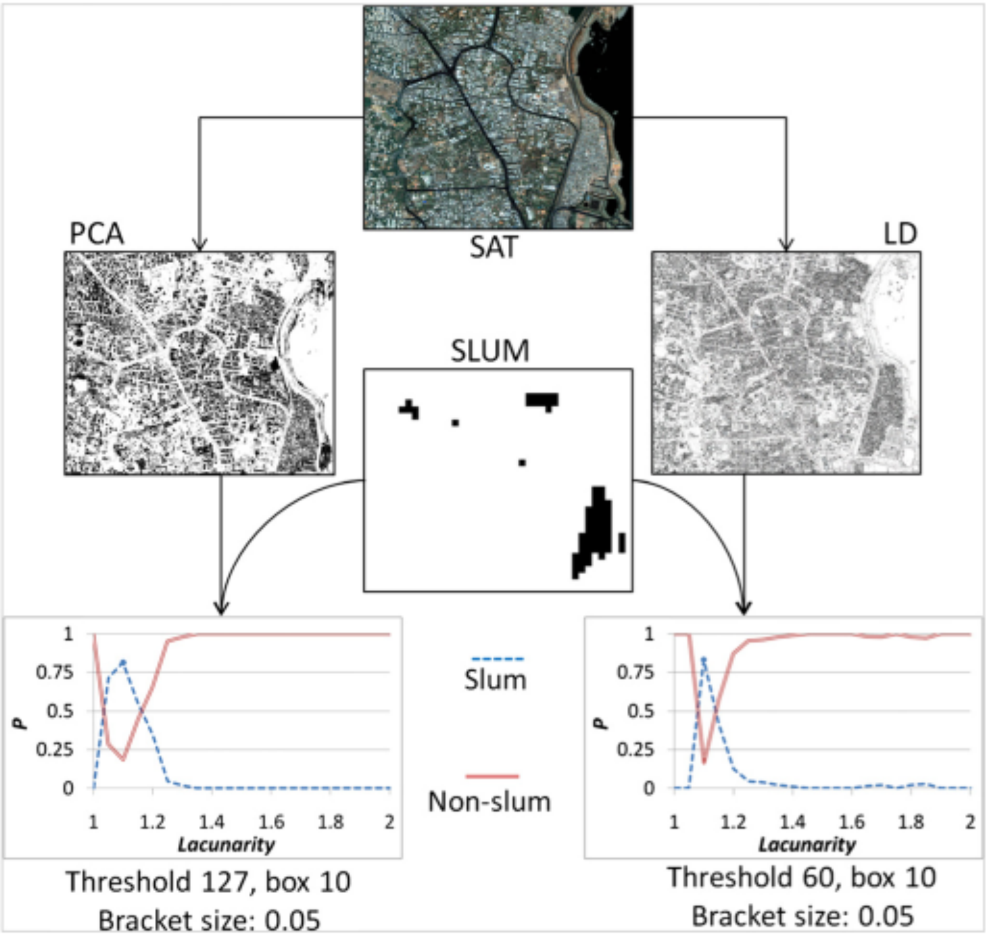

Fig. 3. Slum detection flowchart.

2010. Using this data, an area in the central part of the city was selected and classified as a slum/non-slum matrix (box SLUM in Fig. 3). This matrix was then compared to computed lacunarity results and used to calculate identification confidence for each binarisation threshold and floating window size. The bottom part of the Fig. 3 contains the resulting charts that plot slum identification probability against lacunarity and describe three lacunarity ranges:

- < 1.1: very strong signal, the probability of a cell not being a slum heads to 100%.
- 1.1 to 1.15: strong signal, the probability of a cell being a slum is high;
- > 1.15: very strong signal, the probability of a cell not being a slum heads to 100%.

The calibration results indicate that a line detection algorithm delivers consistently better results than principal component analysis and is particularly good at a 10 pixel floating window size and 60 binarisation threshold. This combination of parameters suggests that the highest correlation between calculated and observed slum locations occurs at lacunarity values 1.10 to 1.15, with identification probability reaching 83.33%. This agrees with findings of Malhi & Román-Cuesta, 2008, stating that lower lacunarity values refer to denser settlement and hence higher slum probability. The size of the optimal floating window is also consistent with our initial assumption that average dwelling unit size in slums falls into 3–6 m bracket.

In order to test the accuracy of the chosen approach the method was validated by the means of analysis of different subsets of the QuickBird scene covering other parts of the city which were also studied during ground truthing visits. The algorithm has identified several areas within the subset where lacunarity values fluctuated between 1.10 and 1.15. The georeferenced street-level photographs taken both in these areas and outside them show substantial differences in housing types and generally support slum/non-slum classification made by the slum detection algorithm. Fig. 4 summarises the results of the algorithm validation procedure and shows two different subsets of the original satellite image together with georeferenced photographs taken during field surveys.

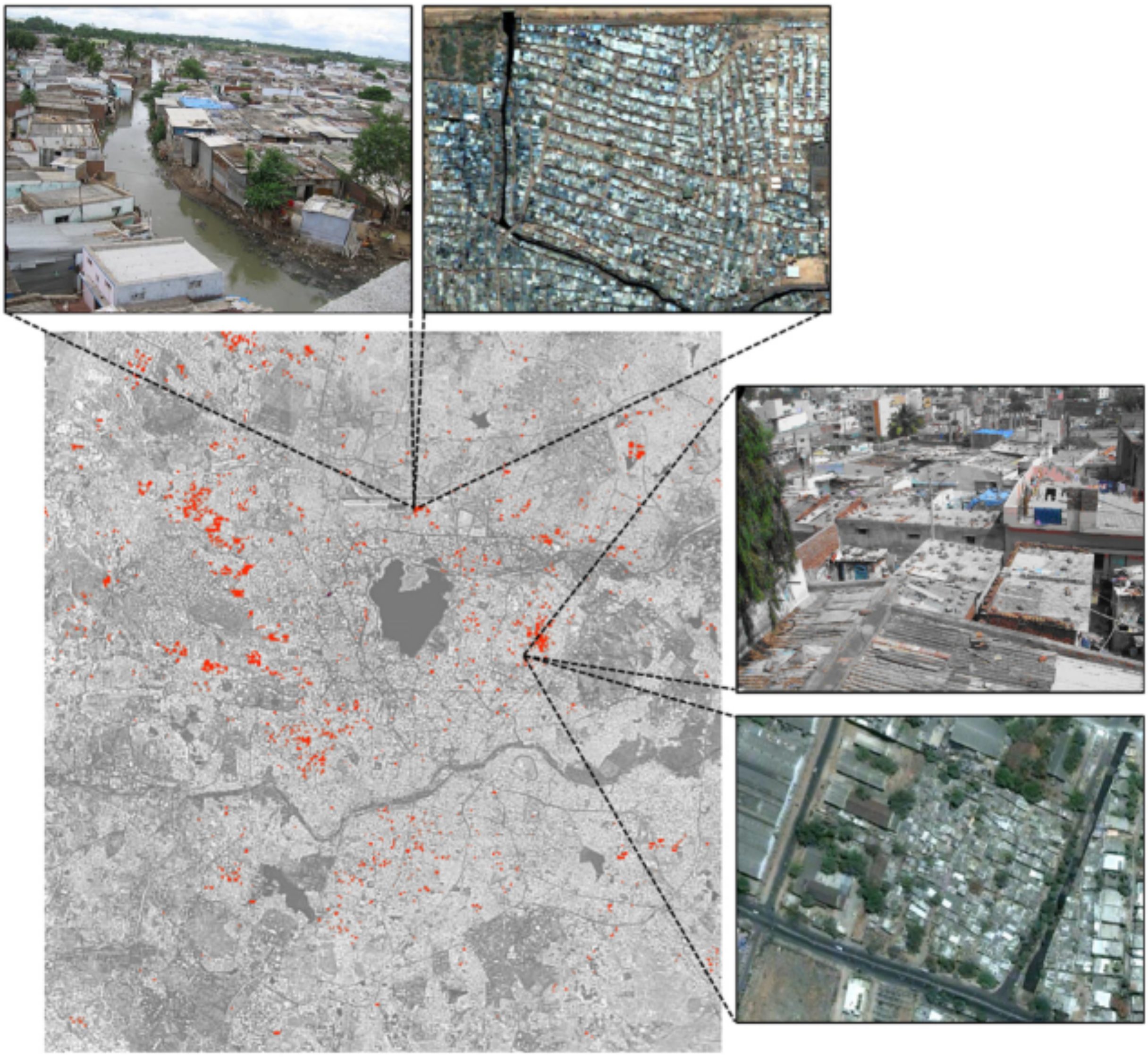

Fig. 4. Slum Locations in Hyderabad (red areas) and georeferenced field photographs of Rasolpoora slum in the northern and Nagamiah Kunta slum in the eastern part of the city (photo credit: Martin Budde/PIK). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Discussion

The sub-metre satellite imagery appears to be a suitable data source for identification of slums in Hyderabad using advanced image analysis techniques. While the resolution might be sufficient for manual image processing (e.g. Baud et al., 2010), such an approach would be of little use in operational monitoring circumstances under limited availability of time and human resources. The specific spatial structure of slums in terms of object density and heterogeneity suggests the use of lacunarity as a measure of surface texture for their detection. The lacunarity matrix computed for the city of Hyderabad contains a number of records which fall into 1.10 to 1.15 range – a value bracket which covers the overwhelming majority of slums within the calibration subset. This interval is also supported by Malhi & Román-Cuesta, 2008, who state that lower lacunarity values refer to denser settlements and hence to higher slum probability. The street-level photography of additional validation areas confirms the presence of slums in the areas characterised by lacunarity values 1.10 to 1.15 as well.

Further visual comparison of the lacunarity map and satellite image has shown, however, that approximately 10% of cells with lacunarity values lying in range 1.10–1.15 were placed over the parts of the city which clearly contained no slums. Such areas included water bodies and some green spaces – areas, whose binary signatures might have resembled those of a slum in terms of feature density and structure. Due to their distinctive spectral signatures, water bodies and green spaces can be reliably identified and masked by an unsupervised imagery clustering procedure, which has recently been found to be able to deliver sufficient accuracy for studies where the collection of representative signatures is not feasible or the terrain being mapped is particularly heterogeneous (Rozenstein & Karnieli, 2011). This approach is already earmarked for use in future research and has great potential to further improve slum detection quality, at the same time eliminating the majority of erroneously classified cells.

The performance of the lacunarity-based slum detection algorithm greatly depends on the technique employed to prepare binary datasets used in the calculation. It has been observed that the calibration dataset correlates better with the lacunarity matrix computed using line detection-based binary source that to the PCA-based one. We assume that this is caused by the fact that line detection routine as implemented by Martinez & Cupitt, 2005, already pre-outlines individual objects within the satellite image and hence creates a more suitable environment for the lacunarity algorithm to work in.

This work acknowledges the fact that lacunarity is an aggregate function and as such produces raster grids with one cell representing the spatial heterogeneity within a certain matrix. Given the 60-cm scale of satellite imagery, typical 100 × 100 pixel matrix translates into 3600 m^2 square polygons. Since the boundaries of informal settlements seldom correspond to lacunarity grid cells, the method can potentially misplace or misidentify slums covering smaller areas. Hence, the method performs best in identifying slums larger than 3600 m^2 threshold.

More generally, the use of lacunarity-based slum identification in urban decision making addresses the responsibility of the authority to provide for all citizens it serves, irrespective from their social class or living area. The ability to rapidly detect slums using high resolution imagery hence creates an opportunity to address new developments in the city in a timely and appropriate manner.

Summary and conclusions

Sustainable urban planning and management require land use data which reliably represent the urban fabric at any point in time up to the present. We have suggested a technique for detection of urban slums using remote sensing data and lacunarity-based pattern recognition. The methodology is capable of rapidly creating a coherent dataset describing the majority of informal settlements in the city of Hyderabad irrespective of technical (lighting conditions, season, and manpower availability) and political limitations. The resulting map agrees with the scattered body of knowledge on slum locations in various areas in the city, such as Rasolpoora slum near the military airport, slum fields around industrial estates of Patancheru in the north-west of the city, the high density of informal settlements within unclaimed land on the banks of drainage channels.

The methodology outlined in this paper will be used in subsequent studies looking at the dynamics of slum growth in Hyderabad by analysing multi-temporal very high resolution imagery. The resulting map of informal areas will also be used to assess the degree of vulnerability to climate change-induced extreme weather events and to ultimately suggest the most important adaptation measures. Since the method makes use of generalised urban morphology rather than specifically local features, it has the potential for successful use in other cities in developing world. The fact that no proprietary software is being used in the whole image processing and slum identification process makes the methodology particularly suitable to be used in cities with limited resources.

This paper presented an algorithm which is verified to be capable of identifying slums in Hyderabad (India) using very high resolution remote sensing data. We found that slums in Hyderabad occupied a total area of 6.4 km^2 or approximately 1.6% of the total area in 2003. Slums are high density settlements, with a typical average urban population density of 22,000 persons/km^2 for India (Baud, Pfeffer, Sridharan, & Nainan, 2009). 6.4 km^2 of slum can hence host up to 140,000 slum dwellers. The majority of identified slums in Hyderabad were located on the edge of the city, particularly near the industrial areas of Patancheru and Secunderabad.

While the identified slum population figures for Hyderabad are significantly lower than the official data (see Table 1), it should be noted that the outlined methodology does only rely on the structural characteristics of a slum and the results cannot be directly compared to the much broader and often politically biased definition of a slum in India. Slums are very dynamic and often patchy forms of urban fabric which frequently undergo slum upgrading processes. The lacunarity algorithm is hence capable of identifying the core of a slum, the very area with particularly dense and jammed housing that is particularly vulnerable to natural and socio-economic hazards. The advantage of this approach is that it gives urban managers the option to increase the efficiency of their often very limited resources and to target support and improvement measures at those particularly in need. The relatively low hardware requirements and absence of software licensing costs also make the technique feasible for use in developing countries.

We expect the lacunarity algorithm to be capable to identify slums in other areas of the world and invite researchers working in the field to collaboration.

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