

The capabilities of remote sensing to derive urban location factors for probability-based spatial growth analysis

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1 ABSTRACT

Urbanization is arguably the most dramatic form of irreversible land transformation. Though urbanization is a worldwide phenomenon, it is especially prevalent in India, where urban areas have experienced an unprecedented rate of growth over the last 30 years (UN, 2007). This paper focuses on the capabilities of remote sensing to identify and derive spatial urban location factors which influence future urban growth. We utilize multitemporal remotely sensed data sets from Landsat and TerraSAR-X sensors as well as a digital elevation model (DEM) from the Shuttle Radar Topography Mission (SRTM).

The land cover of the test site, the highly dynamic incipient mega city of Hyderabad in India, was classified and a change detection analysis was performed to monitor the dimension and the spatial configuration of urban growth since the 1970s. The results of the change detection as well as the DEM serve as basis to derive and develop spatial location factors influencing urban growth. Parameters like the slope, the major street network, continuous intra-urban open spaces, main direction of growth, etc. were calculated. Furthermore external data sets on locations of commercial centers, airports, etc. were integrated. Based on regional theory for every single parameter a specific hypothesis was stated. For example: We assumed that high slope gradients have a lower probability for future settlements or that new commercial centers have a positive influence for future settling. In addition, results from a comparative study of the 12 largest Indian cities (Taubenböck et al., 2009), like saturation effects for built-up density, were integrated as additional information.

An approach combining all urban location factors for the metropolitan area of Hyderabad was developed to identify areas that are theoretically highly probable for future settlements. The approach was applied to the spatial physical extension of the urban area of 2001, the so called urban footprint. Accuracy was assessed for predicted areas of urban growth comparing the result to the actual urban footprint acquired in 2009. The results of the method basically showed high probabilities for those areas which actually have experienced growth, but the limitations of the approach revealed low absolute accuracy. This is due to the manifold parameters having an impact on spatial growth – e.g. socio-economic, physical, demographic or political parameters – which could not be derived using remotely sensed data. Thus, the method basically enables location study to differentiate between preferred and unlikely areas of future urbanization.

2 INTRODUCTION

For the first time in human history, in the year 2006, more people were living in cities than in rural areas (UN, 2007). This is the result of high urbanization rates in the last decades, especially in less developed countries. This trend will be continued in the near future. The United Nations (2007) estimate that in the year 2050 70 % of the world's population will live in urban areas, with a total population growth from 6.7 to more than 9 billion people. In the same time the urban population will increase from 3.3 to 6.4 billion people. Very high growth rates have been observed in India, where the total population has doubled during the last 50 years, while the urban population has grown nearly five times (Taubenböck et al., 2008). The number of Indian mega cities – cities with more than 10 million inhabitants – will increase from the current three (Mumbai, Delhi, Kolkatta) to six by the year 2021 (new additions will be Bangalore, Chennai and Hyderabad), when India will have the largest concentration of mega cities in the world (Chakrabati, 2001).

In general, the emergence of mega cities is not a problem per se. The dynamic urbanization only creates negative effects, if it fails to control the structural development, to finance the necessary public infrastructure (electricity, potable water, waste management, schools, hospitals, etc.) and to control the social, economic and environmental impacts of fast growing cities (Keiner & Schmidt, 2003). However, the explosive urbanization often disables sustainable development, which results in unplanned and uncontrolled urban growth.

The basis for sustainable development strategies lies in the observation and understanding of the urbanization process. Sustainable development needs information about the characteristic properties of spatial growth, like growth rate, direction and pattern (Taubenböck et al., 2009). Remote sensing is able to provide such information and to measure spatial development for a long period of time.

The observation and extraction of information about the state of development in urban areas is the basis to forecast the future development of metropolitan regions. During the last years models of land use change and urban growth have been expanded and have become important tools for city planners, economists, ecologists and resource managers to support intelligent decisions” (Herold et al., 2001). In this study we investigate the capabilities of remote sensing to derive factors that characterize and influence spatial urban location to identify suitable and probable areas of future urban growth. Furthermore we test a straightforward forecast model using location factors to assess future spatial development of the Hyderabad metropolitan region. We aimed to address several specific questions:

- Which urban location factors relevant to location theory can be derived from multi-sensoral medium resolution satellite data?
- Are we able to assess preferable and unlikely areas of future urban settlements combining remotely sensed data and a simple urban growth model?

2.1 Literature review

Remote sensing techniques can provide information about land cover with a high level of detail as well as high temporal frequency and has already shown their value in mapping urban areas (Herold et al., 2003; Jürgens, 2001, 2003; Maktav et al., 2005; Taubenböck et al., 2009). Besides the observation of a status at a particular time, remote sensing provides also the possibility to observe the development of an investigation area by change detection (Lillesand & Kiefer, 2004). Spatiotemporal analysis using time series of remote sensing data enables the derivation of urban footprints, thus to monitor and quantitatively describe the urban structure and development (Herold et al., 2003; Lucas et al., 2007; Taubenböck et al., 2009). Through the observation and analysis of the spatial development preferred growth areas can be identified and location factors (Push- and Pull-factors) for the future urban development can be derived (Heineberg, 2001). Such factors shall be obtained in this study and are to be combined with the existing remote sensing data in an urban growth model.

During the last years urban growth models have become important and innovative tools for city planners and decision makers. The increased attention is based on enhanced remote sensing data and improved computer technologies. However, the application, performance, and outputs of urban growth models depend strongly on the quality and type of the data available for parameterization, calibration and validation (Herold et al., 2003). There are different approaches to model urban growth, the main are Cellular Automaton (CA), Artificial Neural Network (ANN) and traditional statistical models. CA-based models offer many advantages. Their decentralised approach, the link they provide to complexity theory, the connection of form with function and pattern with process, the relative ease with which model results can be visualised, their flexibility, their dynamic approach, and also their affinities with geographical information systems and remotely sensed data (Torrens & O’Sullivan, 2001). Among others, Clarke et al. (1997), Clarke and Gaydos (1998), Alkheder et al. (2006) and Herold et al. (2001) have used CA-based modeling approaches. ANN-based models were developed to model the brain’s interconnected system of neurons so that computers could be made to imitate the brain’s ability to sort patterns and learn from trial and error, thus observing relationships in data (Pijanowski et al., 2002). The learning ability is the great advantage of ANN-based models with respect to other modeling approaches. For instance, Liu et al. (2005), Pijanowski et al. (2002), Liu and Seto (2008) and Jain and Feyissa (2008) have used ANN-based modeling approaches. Traditional statistical models are the oldest approaches to model urban growth, e.g. Markov-chain analysis and

Regression analysis. For more information we refer to Baker (1989), Cheng and Masser (2003), Jahan (1986), Muller and Middleton (1994), Theobald and Thompson Hobbs (1998), Weng (2001) and Wu et al. (2006).

2.2 Study area and data

2.2.1 Study area

Hyderabad is the capital of the Indian State of Andhra Pradesh. The sixth largest City of India is a sprawling metropolis with a population of 6.4 million in 2007 and a current growth rate of 2.3 percent per year. The city's population is expected to achieve 14 million in 2021 turning it into one of the megacities of tomorrow (City Development Plan-Hyderabad, 2001). There are a number of industrial estates, three directly in the Hyderabad district and about 19 in the Rangareddy district belonging to the Hyderabad agglomerations which were mainly established between 1975 and 1985. Main industrial sectors include chemical and bulk drug, metals, timber, plastics, rubber and textile industry as well as electronic industry. Hyderabad hosts several major companies and public sector enterprises with central research and training institutions as well as universities and professional colleges. The dynamic city has emerged as a knowledge hub making rapid strides in information technology („Cyberabad“), biotechnology and medical care but also in tourism (Taubenböck et al., 2007).

2.2.2 Data

In this study we utilized remote sensing data of the Landsat and TerraSAR-X sensors. The Landsat program represents a series of earth observation satellites that have been continuously available since 1972. It started with the Multi-Spectral-Scanner (MSS) featuring a geometric resolution of 79 meters and a spectral resolution of four bands (green, red, two near infrared bands). Since 1982 the Thematic Mapper (TM) has operated with 30 meter geometric resolution and seven spectral bands. Since 1999 the Enhanced Thematic Mapper Plus (ETM+) has operated with an additional panchromatic band at 15 meter geometric resolution. The radar satellite TerraSAR-X, developed in a public-private-partnership between the German Aerospace Center (DLR) and EADS Astrium GmbH, was launched in 2007 and supplies high-quality radar data for purposes of scientific observation of the Earth (DLR, 2007a). TerraSAR-X has three scanning modes (ScanSAR, StripMap, SpotLight, high resolution SpotLight) with a geometric resolution between 16 meters in ScanSAR mode and 1m in high resolution Spotlight mode (Herrmann et al., 2007). For the analysis of the urban area of Hyderabad we used Landsat data of the years 1975, 1989 and 2001 and TerraSAR-X data of the year 2009 acquired in StripMap mode with a geometric resolution of 1.55 meters. In addition, we used a digital elevation model (DEM) from the Shuttle Radar Topography Mission (SRTM), with respect to the topographic circumstances of the Hyderabad metropolitan area. Figure 1 shows the intensity image of the radar signal for Hyderabad with bright pixels indicating urbanized areas. A full coverage of the sprawling metropolis required three TerraSAR-X scenes.

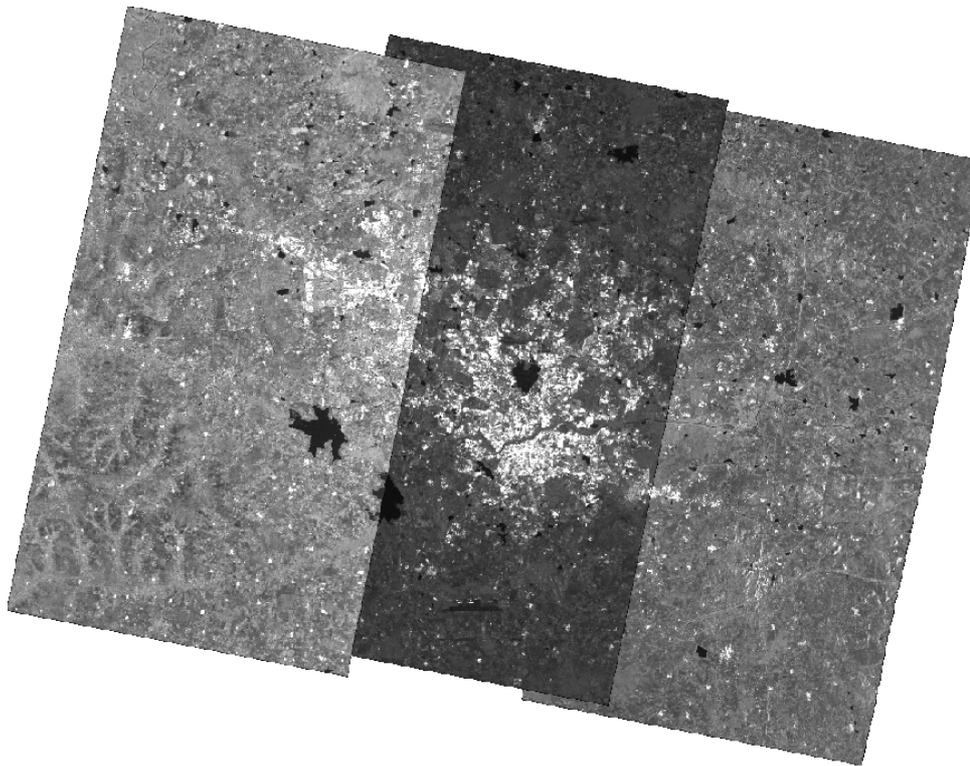


Fig. 1: TerraSAR-X data Hyderabad 2009

3 METHODS

3.1 Time-Series analysis using multi-temporal and multisensoral remotely sensed data

This study focuses on the capabilities of remote sensing to derive physical location factors that allow characterizing the urban landscape on a regional geometric level in theoretically favoured and non-favoured areas. We assume that these location factors enable to identify suitable and probable areas of future urban growth.

The basic spatial land-cover information is derived for different time steps using all available remotely sensed images – Landsat and TerraSAR-X data. A hierarchical, object-oriented classification methodology is implemented extracting the thematic classes ‘built-up areas’, ‘non built-up areas’ and ‘water’ separately from all optical Landsat images. The object-oriented methodology was used to combine spectral features with shape, neighbourhood and texture features (Clodt, 2009; Taubenböck et al., 2009). A pixel-based classification approach is used to extract urban and non-urban structures from a single TerraSAR-X image. The urban footprint is extracted by analysing the speckle characteristics of a TerraSAR-X scene based on an estimation of the local coefficient of variation and the fading texture of the whole scene. The basic concept is to extract reliable urban features, which are represented by bright point scatterers (corner reflectors). The so called urban seeds depict especially the reflection information about vertical structures. To derive the urban footprint image analysis techniques are used to densify the detected urban seeds. We used an optimized threshold procedure, which extracts urban seeds from the original intensity image and a strongly smoothed speckle divergence with a 35x35 window. As a further optimization we estimated the final urban footprint with smoothed speckle divergence and smoothed urban seeds (Esch et al., 2010). The post-classification spatial overlay and intersection of the classified urban footprints for the years 1975, 1989, 2001 and 2009 allows the retrieval of quantitative information about the spatial development of the test site, e.g. dimension of urban growth, growth directions or built-up density. The focus in this paper is on the time interval 2001 – 2009, for the other years we refer to Taubenböck et al. (2007, 2009). Figure 2 displays the change detection for Hyderabad from the 1970s until today.

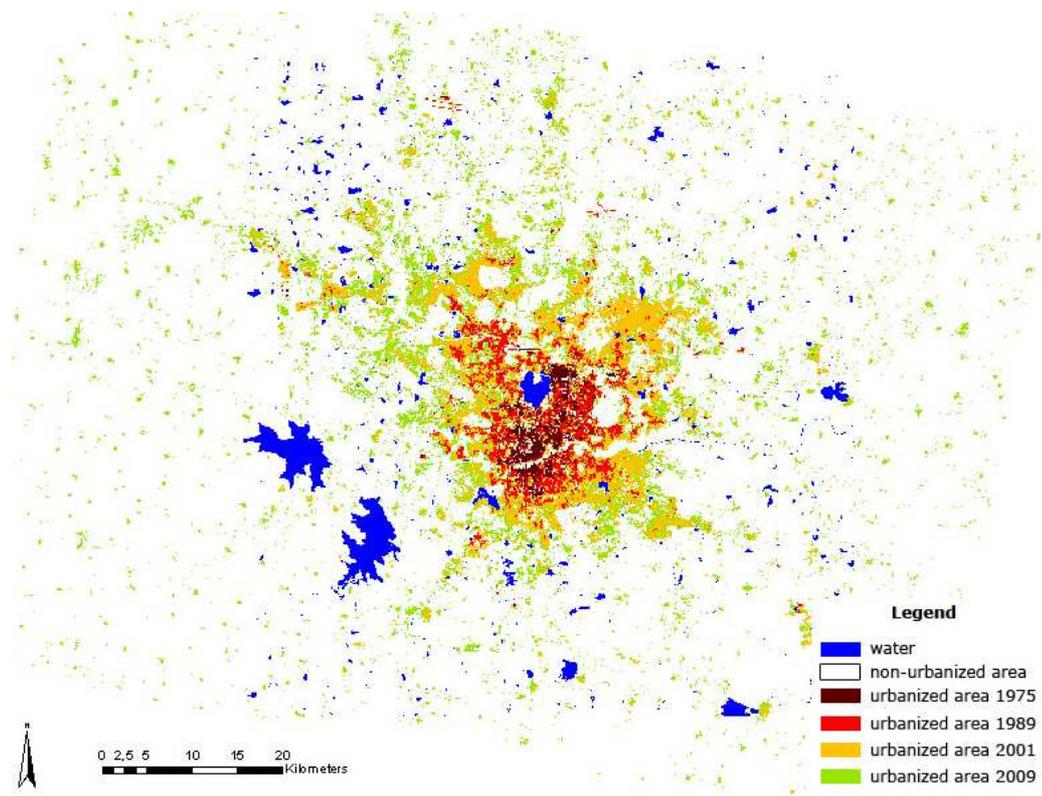


Fig. 2: Change Detection Hyderabad 1975-2009

3.2 Development of urban location factors

The results of the change detection as well as the DEM serve as data basis to derive and develop spatial location factors influencing urban growth. Parameters like the slope, the major street network, continuous intra-urban open spaces, main direction of growth, etc. were calculated. Furthermore, external data sets on locations of commercial centers, airports, etc. were integrated. Based on a regional theory for every single parameter a specific hypothesis was stated. Overall, three categories of urban location factors have been derived:

- Topographic environmental layers
- Location bound layers
- Continuous intra-urban open spaces

The hypotheses we state regarding the different urban location factors arise from studies in the field of urban growth modelling (chap. 2.1), the polarization theory of city development, push- and pull-factors (Heineberg, 2001) and characteristic features that influence urban growth (e.g. accessibility). The topographic factors include the DEM and slopes of the earth's surface. For these two factors we state the following hypotheses:

1. The terrain height influences probability for settlements
2. Steeper slopes decrease probabilities for new settlements.

The location bound factors comprise buffers with increasing distances to the urban core, the major street network, industrial areas, airports, etc. Furthermore we use urban growth sectors, which define preferred directions of growth. We state the following hypothesis regarding the location bound factors:

3. With increasing distance from the city core the built-up density decreases.
4. With increasing distance from the city core the probability for new settlements decreases (cp. Fig. 3a)
5. Already existing dominant growth directions serve as pull-factors for settlements (cp. Fig. 3b & 4)

As an example, we divided the metropolitan area of Hyderabad into 16 sectors (directions). Thus, we use the change detection between 1975 and 2001 to learn from the past spatial development of Hyderabad to identify, calculate and define preferred directions and locations of growth.

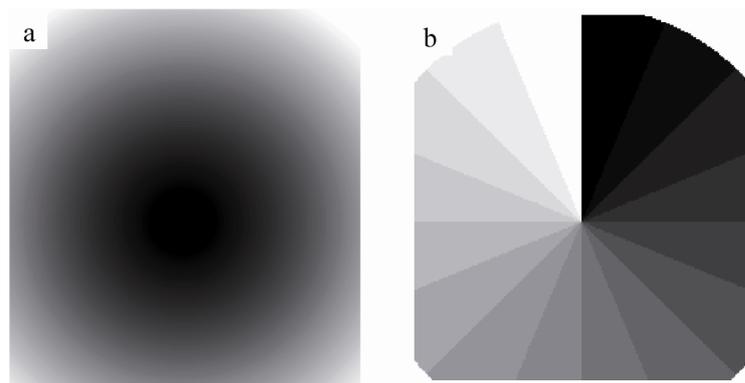


Fig. 3: Two environmental layers: a) buffer b) urban growth sectors

Furthermore, the major street network and industrial areas of the Hyderabad metropolitan area were derived. For this purpose we used the TerraSAR-X data, an analogue map on the street network (Gotsch/Kothe, 2008) and Google Earth as reference. These two factors were implemented in the urban growth model with the following hypotheses:

- 6. The street network is a pull-factor for future settlements
- 7. Industrial areas are pull-factors for further industrial development

These pull-factors induce a stronger weight of these areas in the urban growth model. The change detection of Hyderabad revealed as third category of location factors temporal continuous intra-urban open spaces, which have not been urbanized between 1975 and 2009. Thus, we assumed that these places are restricted areas and nonrelevant for future urban growth (cp. Fig 4).

The hypotheses and their related layers have to be transferred into location-based probability assessments for future urbanization. The idea is to estimate the target distribution by finding the distribution of maximum entropy, subject to the constraint that the expected value of each feature under this estimated distribution matches its empirical average (Phillips et al., 2004). We use the open source software MaxEnt (<http://www.cs.princeton.edu/~schapire/maxent/>) to compute location-based probabilities for input variables. The urban footprint of e. g. the year 2001 serves as input variable or training data set. Using Bayesian theory (Richards & Jia, 1999) the training samples are calculated in statistical combination with the information of the sample environmental or location bound layer. Thus, for the example of the growth directions, the maximum-entropy-method learns in an iterative process the dominant sectors and assigns to non-urbanized areas relative probabilities of future urban growth.

The computation of pull-factors influencing parameters for urban growth, like e. g. the major street network, are based on buffers. Within these buffers we assign decreasing growth probabilities with increasing distance to the street network. This kind of weight calculation has been done for all layers, except the intra-urban open spaces layer which have been left unmodified. This layer will be used to exclude these defined areas from the modeling result. Figure 4 shows sample results for the computation of transferring the different thematic layers into location-based probability assessments.

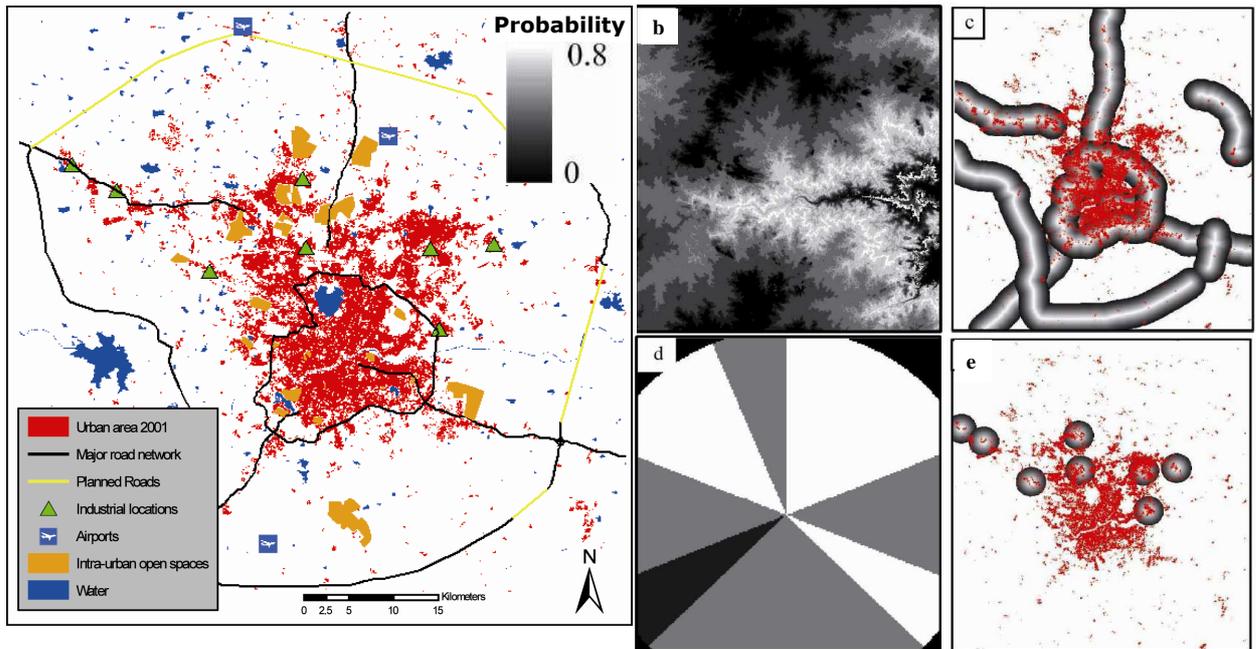


Fig. 4: a) Location bound environmental factors; calculated probabilities for settlements regarding the DEM (b), the pull-factor highways (c) the main directions of growth (d) and the pull-factor of major industrial sites (e)

3.3 Probability-based urban growth analysis

Based on location theory, the assessment of appropriate and thus probable areas for future urban growth is calculated. A probability-based approach is implemented using an additive approach. The additive approach combines the multiple hypotheses (the modeling results for individual location factors) adding up all computed probabilities on a pixel-level (cp. Fig. 5). Furthermore, additional structural information on urbanization in India is integrated using results from a different study (Taubenböck et al., 2009). This study revealed saturation effects in the urban cores regarding built-up density in the 12 largest cities in India. Thus, our model does not allow, independently from the probability values, urbanization in the urban core, if built-up density exceeds 80 %. After addition of the probability values, the areas with the highest growth probabilities are identified and selected for urbanization.

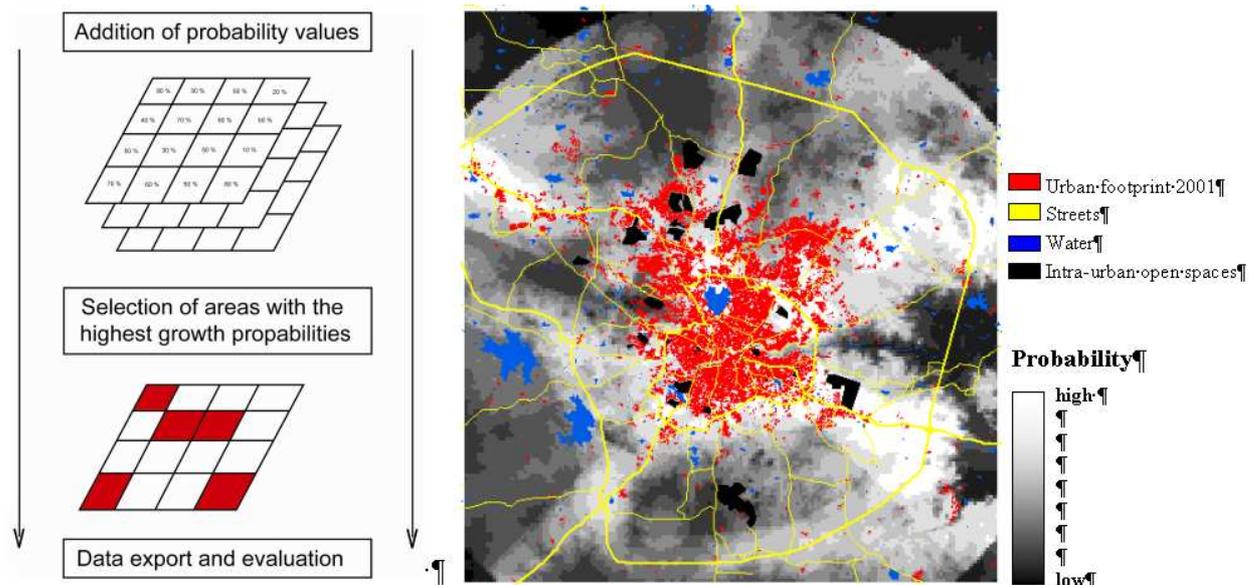


Fig. 5: Schematic representation of the additive modeling approach

4 RESULTS AND DISCUSSION

The result of the urban growth assessment process is shown in Figure 6. It was produced with the additive urban growth model introduced in section 3.3 and was calibrated with all thematic layers introduced in

section 3.2. It is shown where the highest probabilities for future urban growth for the metropolitan area of Hyderabad is calculated (Fig. 5). The result shows highest probabilities for urban growth in a ring near to the center of Hyderabad as well as at focal points in the near suburban areas, in the North-West, South-West and South-East of the city. Densification in the urban center is restricted by the 80% built-up density constraint. An accuracy assessment was performed to verify the classification as well as the growth assessment results.

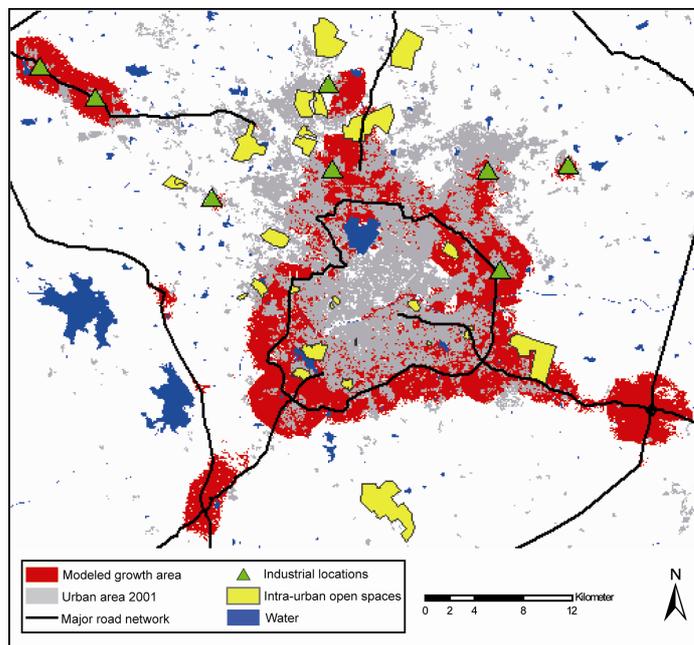


Fig. 6: Modeled urban growth

The accuracy assessment was done in two parts: The first part focuses on the validation of all input data derived from remotely sensed imagery. Therefore the three extracted land cover classes (built up areas, non-built up areas, water) were compared to reference data separately. High resolution Quickbird data (2005) as well as Google Earth (2008) were used as reference. The accuracy assessment was performed with 200 randomly distributed control points for each class, and was quantified in an error matrix by visual comparison. The overall accuracy for the classification of the TerraSAR-X data 2009 for Hyderabad is 96 % correctly classified pixels. The Landsat classification 2001 for Hyderabad, which was used as starting point of the urban growth model, reaches an overall accuracy of 85,75 % (Pengler, 2007).

The second part of the accuracy assessment analyses the growth prediction of the additive approach. The validation was performed with 2 methods: The first method calculates the absolute accuracy of the modeling result. Thereby, we intersected the modeled urban growth with the real urban growth derived from the remote sensing database. The absolute accuracy of the assessed urban growth is 23.6 % correctly modeled pixels.

The second method compares the modeled growth areas and the real growth areas derived from remotely sensed data for defined spatial sectors. By deviding the urban area into 16 growth areas (cp Fig. 4b) it is possible to analyse the accuracy of the modeling results with respect to reference areas. Thus, the accuracy is assessed without the requirement of being absolutely correct in absolute locations. For it, we compared the modeled growth area with the real growth area in every single sector. The accuracy of the spatial analysis ranges from 23 % to 320 % correctly classified pixels. The result shows in nine of sixteen areas an overclassification or an under-representation of assessed urbanized pixels. In seven of sixteen growth areas we have a satisfying accuracy with a range between 80 % and 112 % correctly modeled pixels.

Furthermore, the growth assessment result is assessed statistically based on the calculated probability values and the growth measured in reality between 2001 and 2009. The result shows that the pixels having faced urbanization in reality show a mean growth probability of 52 %. Furthermore, half of the real growth areas reach growth probabilities between 52 % and 73 %. In our approach, only pixels were assigned as possible growth values reaching 73 % growth probability and more.

The result reveals that the areas experiencing growth in reality definitely gain high urbanization probabilities. The straightforward additive approach excludes most of these areas, due to the fact that other areas get, based

on location theory, higher probabilities. A further development related to the integration and preparation of environmental layers and an interdisciplinary extension (e.g. social components) of the additive growth model can contribute to a better urban growth modeling result. First of all, the quantity of urban growth factors offers good opportunities for an enhanced urban growth model with respect to other studies in the field of urban growth modeling (cp. Chap. 2.1).

The accuracy assessment shows that the absolute accuracy to predict urban growth of this approach is only 23 %. Thus, it reveals that the idea of using location theory on an urban footprint level does not do justice to the complex reality in urban areas, where decisions for new settlements or even uncontrolled urban sprawl are based on manifold reasons –political, socioeconomic, personal, ecological, etc. On a closer look, the accuracy assessment also reveals that the areas which were urbanized in reality in the considered time frame show a high urbanization probability based on the location theory. Thus, the spatial analysis on urban footprint level using remotely sensed data is one essential brick within the manifold impact factors that have to be considered for urban growth modeling.

5 CONCLUSION

Recapitulating the two research questions we defined earlier in the introduction (1) “Which urban location factors relevant to location theory can be derived using multi-sensoral medium resolution satellite data?” (2) “Are we able to assess preferable and unlikely areas of future urban settlements combining remotely sensed data and a simple urban growth model?” we can conclude: (1) Multisensoral remote sensing has the capability to provide independent, up-to-date, multitemporal and area-wide spatial location factors for such dynamic areas as incipient megacities with high accuracies. Thus, the products are appropriate on regional geometric level to quantify the urban patterns over time as basis for location studies. (2) The additive approach to assess areas appropriate for future urban growth allows an area-wide location analysis, reveals high probabilities based on location theory for areas of urbanization in reality, but fails to predict reality with absolute high accuracies. The capability of remote sensing to provide not only information on the regional scale used in this study, but also on individual building level allows a thematic progression for location-based analysis. Furthermore, the capability of remote sensing to indirectly infer information on e. g. population distribution, socioeconomic parameters or land use aims at a more holistic data base for understanding the complex urban systems and opens up a wide field to improve this straightforward approach to assess appropriate areas for future settlements.

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