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Spatiotemporal urbanization processes in the megacity of Mumbai, India: A Markov chains-cellular automata urban growth model

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A B S T R A C T

Several factors contribute to on-going challenges of spatial planning and urban policy in megacities, including rapid population shifts, less organized urban areas, and a lack of data with which to monitor urban growth and land use change. To support Mumbai's sustainable development, this research was conducted to examine past urban land use changes on the basis of remote sensing data collected between 1973 and 2010. An integrated Markov Chains–Cellular Automata (MC–CA) urban growth model was implemented to predict the city's expansion for the years 2020–2030. To consider the factors affecting urban growth, the MC–CA model was also connected to multi-criteria evaluation to generate transition probability maps. The results of the multi-temporal change detection show that the highest urban growth rates, 142% occurred between 1973 and 1990. In contrast, the growth rates decreased to 40% between 1990 and 2001 and decreased to 38% between 2001 and 2010. The areas most affected by this degradation were open land and croplands. The MC–CA model predicts that this trend will continue in the future. Compared to the reference year, 2010, increases in built-up areas of 26% by 2020 and 12% by 2030 are forecast. Strong evidence is provided for complex future urban growth, characterized by a mixture of growth patterns. The most pronounced of these is urban expansion toward the north along the main traffic infrastructure, linking the two currently non-affiliated main settlement ribbons. Additionally, urban infill developments are expected to emerge in the eastern areas, and these developments are expected to increase urban pressure.

Introduction

Urbanization processes are now pervasive, given that more than half the world's population lives in cities. This proportion will increase to over 72% by 2050 (United Nations, 2012). Megacities[2] (Sorensen & Okata, 2011) continue to emerge around the globe (Van Ginkel, 2008), representing powerful engines for economic prosperity and growth, although this growth is accompanied by environmental degradation and loss of biodiversity (Czamanski et al., 2008). Most of this urban growth will occur in less developed countries (Girard, Cerreta, de Toro, & Forte, 2007; Van Ginkel, 2008) and will be particularly pronounced and more rapid than expected in India (Bhagat, 2011; Bhatta, Saraswati, & Bandyopadhyay, 2010a; Chakrabarti, 2001; Kumar, Pandey, Hoda, & Jeyaseelan, 2011), most notably in Mumbai (Taubenböck, Wegmann, Roth, Mehl, & Dech, 2009; United Nations, 2012).

These dynamics often result in urban sprawl, a vaguely and not rigorously defined phenomenon (Bhatta, Saraswati, & Bandyopadhyay, 2010b; Helbich & Leitner, 2009). The conditions for urban sprawl mostly occur in North America (Schneider & Woodcock, 2008) and are only partially transferable to Mumbai. Thus, in the present study, two broad definitions are adapted. Although Brueckner (2000) simply defines sprawl as excessive city growth, Ewing, Pendall, and Chen (2002) distinguishes three key dimensions: a) disperse population in low-density developments, b) disconnected and widely separated constructions and buildings, and c) novel developments beyond the urban core within the city outskirts. When these urban expansions arise in an uncoordinated manner, serious and unsustained consequences for the inhabitants can occur (e.g., Bhatta et al., 2010a; Taubenböck et al., 2012). Residents cannot be provided with basic infrastructure (e.g., sewer tunnels, public transportation systems), which increases congestion

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[2] The United Nations (2012) qualifies urban agglomerations as megacities having at least 10 million inhabitants.

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and the strain on sanitation services. These problems can in turn affect crime rates and socioeconomic disparities and can have a variety of other effects.

Policy makers in megacities face unprecedented challenges with regard to governing, urban planning, and land use management because of the prevailing high dynamic growth. Therefore, knowledge concerning past, current, and future growth plays an important role in the decision-making process (Patino & Duque, 2013; Schneider & Woodcock, 2008). Monitoring growth helps to develop an understanding of past trends and growth patterns, while simulation-based modeling can provide insights into possible future developments. Both complementary approaches are necessary strategies for implementing appropriate actions, including a) formulating better land use policies (e.g., growth boundaries), b) meeting transportation and utility demand, c) providing infrastructure, d) identifying future development pressure points, and e) developing ex-ante visions of urbanization process implications, among others. The long-term effects of these actions may support sustainable development aimed at optimizing available resources and decision making (Burgess & Jenks, 2007; Taubenböck et al., 2012).

An essential prerequisite for better land use planning is information on existing land use patterns and changes over time (Bagan & Yamagata, 2012; Koomen, Stillwell, Bakema, & Scholten, 2007). Significant contributions in this field have been made thanks to the advancement of geographic information systems (GIS) and remote sensing (Bhatta et al., 2010b; Patino & Duque, 2013), both of which have been used to relate land use and cover change (Overmars & Verburg, 2006) to urban growth models (e.g., Mahiny & Clarke, 2012; Estoque & Murayama, 2012; He et al., 2013; Jokar Arsanjani, Helbich, Kainz, & Darvishi, 2013). Earth observation data are valuable for long-term monitoring of megacity expansion, especially mid-resolution imagery data, which are area-wide and are available independent of the study area (Patino & Duque, 2013). Several studies that have analyzed urban growth processes in megacities have been limited to retrospective analysis (e.g., Bagan & Yamagata, 2012; Basawaraja, Chari, Mise, & Chetti, 2011; Bhatta, 2009; Pathan et al., 1993; Schneider & Woodcock, 2008; Taubenböck et al., 2009; Taubenböck et al., 2012). However, apart from mapping the status quo, predictive models are also empirically significant because they assess spatial change consequences (Jokar Arsanjani et al., 2013). Accordingly, several statistical and geospatial models have been advanced, including logistic regression models (Hu & Lo, 2007), Markov chains (MC; Kamusoko, Aniya, Adi, & Manjoro, 2009), cellular automata (CA; Han, Hayashi, Cao, & Imura, 2009), and MC–CA models (Vaz, Nijkamp, Painho, & Caetano, 2012), among others.

Comparing these approaches, Jokar Arsanjani et al. (2013) emphasized that spatial autocorrelation can bias estimates from aspatial regression models (Helbich, Brunauer, Hagenauer, & Leitner, 2012). Moreover, as noted by Hu and Lo (2007), this type of model is less suitable for quantification of change and temporal analysis. In contrast, MCs are spatially non-explicit because they compute the probabilities of land use transitions and the amount of change (López et al., 2001). This clearly contradicts the idea of the inherent genesis of urban growth being a spatial phenomenon. MC models are scarcely applied in empirical studies because of this limitation (see Jokar Arsanjani, Kainz, & Mousivand, 2011). Spatial CA models avoid this limitation of MC (Han et al., 2009; Jokar Arsanjani et al., 2013). Based on predefined site-specific rules mimicking land use transitions, CAs represent local raster-based simulation for modeling urban expansion for discrete time steps (Guan et al., 2011). Despite these appealing properties, CA models lack the ability to account for the actual amount of change. Therefore, coupling the MC and CA approaches (Eastman, 2009) provides a powerful modeling framework in which the shortcomings of each are eliminated. MC quantifies future changes based on past changes, thereby serving as a constraint for CA, which addresses spatial allocation and the location of change (Jokar Arsanjani et al., 2013). Compared to regression analysis, MC–CA models do not rely on comprehensive historic time-series census data, which are often scarce in developing countries. Although Kamusko et al. (2009) and Guan et al. (2011) have reported promising results, most studies have failed to link MC–CA with additional driving forces (e.g., distance-based relationships; see He et al., 2013) that can be integrated as transition potential maps using multi-criteria evaluation (MCE) techniques (Eastman, 2009).

In this brief review, we have emphasized that a strong need exists to investigate spatiotemporal urban growth dynamics in developing countries such as India by means of geospatial simulation models to help governments prepare for the explosion of urban living. Developing countries cannot be expected to replicate the growth trends of developed countries (Van Ginkel, 2008). Consequently, empirical research dedicated to these dynamic urban landscapes is of paramount significance to ensure sustainable development. The present study was conducted to investigate the previous land use change and future patterns of urban growth of Mumbai, one of the largest and fastest-growing megacities in the world (United Nations, 2012). This study merged prospective analyses of the period from 1973 to 2010 and predictive modeling for 2020 and 2030 using MC–CA, along with transition probability maps taken into account by MCE. The following research questions were addressed:

- Which land use categories are most affected by urban expansion? How can the past urban growth process of Mumbai be characterized?
- What growth patterns can be expected within the next two decades from 2010 to 2030? Will the amount of land transformation and conversion that has occurred in the past continue in the future? If so, to what magnitude?

Materials

Study area

Mumbai is located between 18° 53′ and 19° 16′ N and between 72° and 72° 59′ E in western India (Fig. 1). The total urban area is approximately 465 km^2, with a maximum east–west extent of 17 km and a maximum north–south extent of 42 km. It is one of the most vibrant cities in India, as well as the main city of the western state of Maharashtra. The availability of infrastructure supported by the government and local authorities has facilitated its economic prosperity, making Mumbai a leading economic and financial center in the process (Bhagat, 2011; World Bank, 2009). This economic prosperity has also been responsible for its urban growth (Bhatta, 2009). The abundance of different types of transportation options (e.g., the national four-lane Golden Quadrilateral road), and ample electricity, and water supplies have further supported this economic growth.

According to the Indian Census of 2011, Mumbai's population has nearly doubled in the last four decades: since 1971, the population has steadily increased from approximately 5,971,000 to more than 12,478,000 in 2011. With the highest population growth in India, Mumbai currently ranks as the seventh-largest urban agglomeration in the world. The United Nations (2012) has forecasted that this trend will continue, with the population reaching

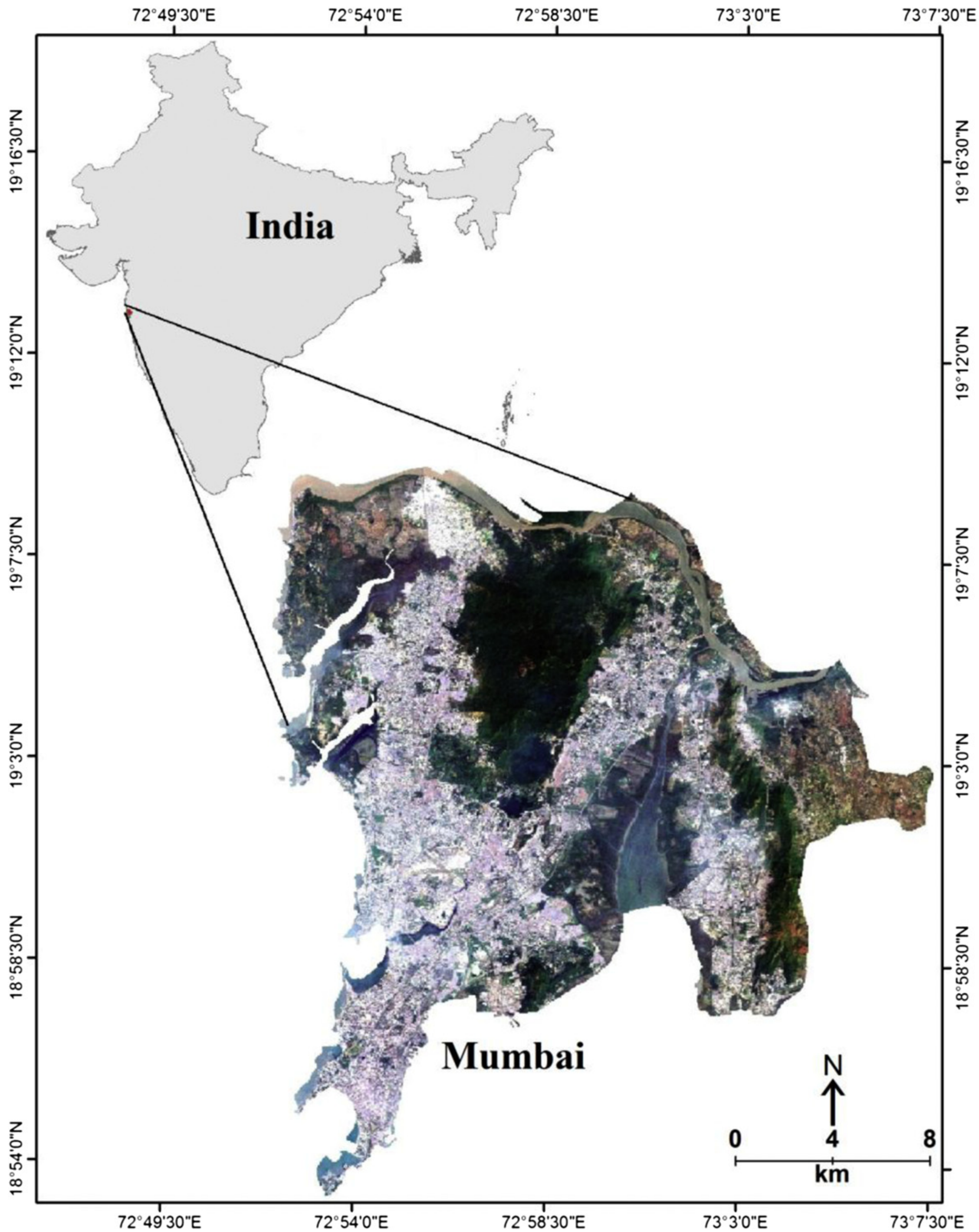

Fig. 1. Location and land cover (true color image) of Mumbai for the year 2010. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

nearly 27 million by 2025, making Mumbai the fourth-largest urban agglomeration in the world.

Data and data preparation

Table 1 lists the datasets that were collected for use in the current study. Landsat satellite imagery was particularly helpful in providing efficient support for area-wide megacity analysis. Both Taubenböck et al. (2012) and Patino and Duque (2013) allude to the fact that Landsat data are cost-effective and maximize the possible temporal monitoring period by keeping the processing time feasible, through their mid-spatial resolution. In addition, Landsat images are frequently updated and are available free of charge through the Global Land Cover Facility repository. This availability makes them ideal for urban growth models. The following Landsat time stamps were gathered for spatiotemporal mapping: 1973, 1990, 2001, and 2010. Given that these remotely sensed images were surveyed by different types of Landsat sensors (i.e., MSS to ETM+), a projection to UTM Zone 43 North, as well as resampling to a common spatial resolution of 30 m, was necessary (the MSS

Table 1
Data sources and types.

Dataset	Source	Date	Resolution
Landsat images (MSS for 1973, TM for 1990, ETM for 2001, and ETM + for 2010)	U.S. Geological Survey German Aerospace Centre	1973, 1990 2001, 2010	30/79 m
Population data	United Nations Census of India	1971, 1981 2001, 2011	n.a.
Digital elevation model	ASTER (NASA)	2009	30 m
Transportation network	OpenStreetMap	2011	vector

sensor has a resolution of 79 m), resulting in a homogeneous time series.

As outlined above, developing countries are faced with data availability problems. This is particularly true for historic time series of socio-economic attributes on a detailed scale. Consequently, this study was limited to population information that serves as auxiliary data. Furthermore, main traffic axes were extracted from the OpenStreetMap (OSM) database donated by Automotive Navigation Data. Basic GIS algorithms were applied to derive slopes and Euclidean distances to water bodies, wetlands, roads, and built-up areas, which were needed to derive subsequent transition probability maps with MCE.

Methodology

In this section, the main components of the urban growth model applied to Mumbai are described. Fig. 2 illustrates an overview of the workflow, which comprised the following stages: a) Classification of satellite images and b) computation of transition probability maps on the basis of auxiliary data, based on MCE. These maps, in combination with the land use maps, were required for the MC–CA simulation model to predict future urban growth for 2020 and 2030.

Extraction of land use maps

Spatiotemporal mapping includes quantitative time series analysis and transformation of land cover classes. Because land use maps are a fundamental prerequisite for modeling future growth, individual land use classes were extracted from the remotely sensed images for each timestamp. After geometric corrections, the land use maps were initially classified based on the maximum likelihood algorithm (Feizizadeh & Helali, 2010). Of prime importance in this study were the footprints of built-up areas, subsuming residential, commercial and industrial buildings, and transportation, among other factors.

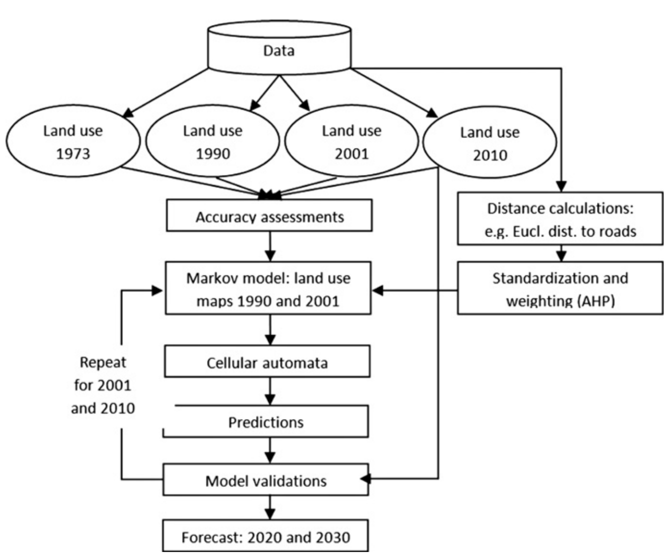

Fig. 2. Workflow for the MC–CA model.

Urban growth model

MC–CA integrates both MC and CA models. The former determines the actual amount of change between land use categories non-spatially. According to López et al. (2001), Markov chains are stochastic process models that describe the likelihood that one state (e.g., cropland) changes to another state (e.g., built-up areas) within a given time period. The resulting probabilities were summarized in a transition probability matrix, not directly transferable to spatial representations.

In contrast, CA is a frequently used spatially explicit model (e.g., Han et al., 2009). As a rule-based model, its topological grid characteristics make CA an appropriate model for incorporating spatial interactions between a cell and its neighborhood. These spatial interactions treat temporal dynamics in discrete time steps (Jokar Arsanjani et al., 2013). For example, assuming a 3 × 3 cell neighborhood, a cell's state is influenced by its eight adjacent cells. The model is constructed using a "bottom-up" approach in which global structures evolve from local interactions between cells by independently varying their states, based on transition rules (Batty, 2005). These models are typically calibrated using training data (i.e., past land use maps), which are then compared with an actual land use map, although the quantity of change is neglected. If statistical evaluation, using the kappa index (Pontius, Huffaker, & Denman, 2004), for example, provides valid results, the calibrated model can be applied to the prediction of future urban spatial patterns (Eastman, 2009).

Despite the limitations of the two types of models, the integration of the two in a so-called MC–CA approach (Eastman, 2009) is empirically sound. CA addresses the spatial allocation and location of change, while MC predicts changes quantitatively, based on the changes that have occurred in the past, after which the values that it predicts are used as inputs to the CA model (White & Engelen, 1997). Previous research by Guan et al. (2011), Jokar Arsanjani et al. (2013), and Vaz et al. (2012), among others, affirms that this technique efficiently simulates urban growth. Guan et al. (2011) also linked the MC–CA model to the analytical hierarchy process (AHP; Saaty, 1990), which allows weighting of land use transition potential on the basis of a set of potential maps (e.g., magnitude of slope), and incorporates growth constraints. The potential maps are typically expressed as fuzzy sets. Based on standardization functions (e.g., a sigmoid function), the values are scaled to a range of 0–1, where 0 represents the least suitable sites and 1 represents the most suitable sites. Eastman (2009) stated that fuzzy sets (Zadeh, 1965) establish a standardized measure and avoid the selection of priori unknown Boolean constraints or cut-off values. Helbich and Leitner (2009) extended this argument and claimed that fuzzy sets were particularly useful when the underlying urban theory is imperfect. AHP, as part of MCE, determines the weights of the (fuzzy) potential maps by means of pairwise assessments (Malczewski, 1999). To access weighting parameters, expert knowledge or qualitative interviews are commonly conducted (see, e.g., Estoque & Murayama, 2012). The meaningfulness and consistency of the weightings must be verified by means of the consistency ratio (Guan et al., 2011). AHP is most helpful when single aspects are complicated to quantify, and the relative importance of each component depends on the others (Malczewski, 1999). Thus, this process allows for narrowing of the

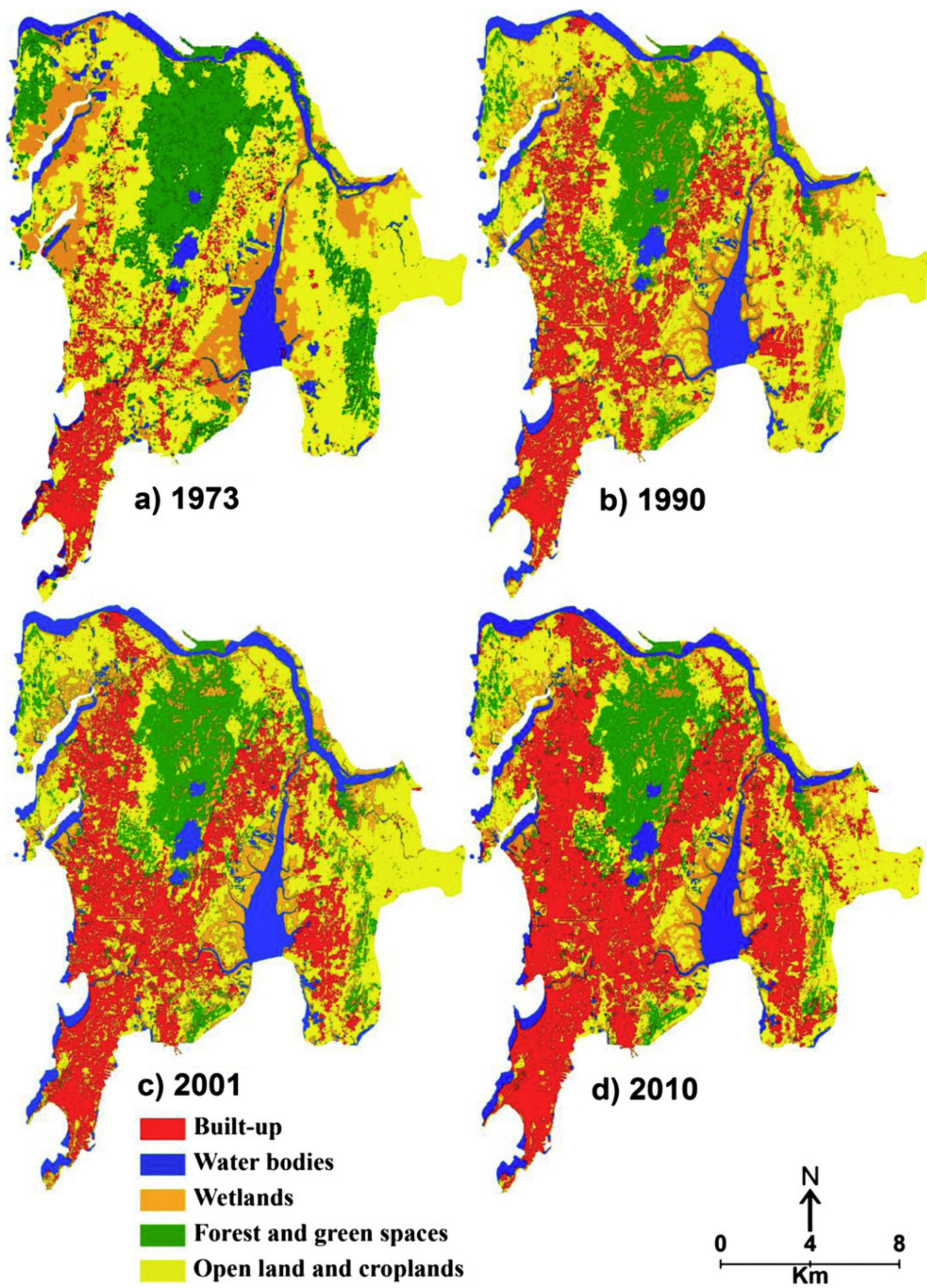

Fig. 3. Time series of land use maps for 1973–2010.

resulting transition probabilities to more precisely reflect the characteristics of the local environment.

Results and discussion

Spatiotemporal mapping of land use changes

The classification process resulted in four land use maps that discriminated among the following five land use categories: built-up areas, open land and cropland, forest and green space, wetlands, and water bodies. Additionally, the classifications were manually improved in a post-processing step. For evaluation of the classification results, a random sample of 250 well-distributed points was extracted before being visually verified with Google Earth, OSM, and official reference maps. Subsequently, statistical confirmation was obtained through the kappa coefficient. The coefficient values ranged from 0.84 to 0.86, thus indicating the suitability of the classified remote sensing images. Similarly, Bhatta

Table 2
Absolute quantities for each land use class (in ha) for 1973–2010.

	Built-up areas	Water bodies	Wetlands	Forest & green space	Open land & cropland
1973	7629	8046	11,992	16,460	43,404
1990	18,455	8271	9734	11,418	39,682
2001	25,498	7805	9086	11,057	34,124
2010	35,607	7100	8187	10,329	26,353

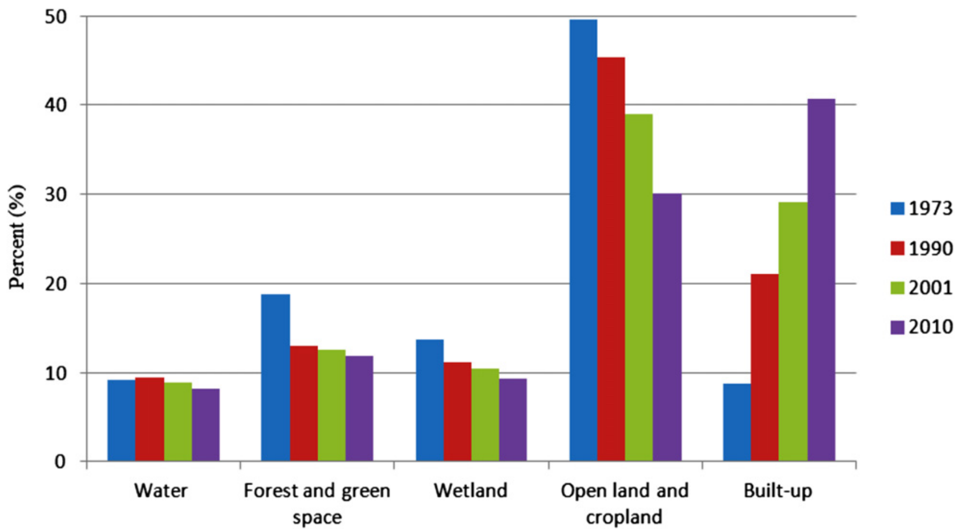

Fig. 4. Temporal changes of land use classes (in %).

Table 3
Population and urban growth for 1971–2011.

Year	Population	Periods	Population growth	Year	Built-up areas (in ha)	Periods	Urban growth rate
1971	5,970,575		Base year	1973	7629		Base year
1981	8,243,405	1971–1981	38.1%	n.a.	n.a.	n.a.	n.a.
1991	9,925,891	1981–1991	20.4%	1990	18,455	1973–1990	142.0%
2001	11,914,398	1991–2001	20.0%	2001	25,498	1990–2001	39.8%
2011	12,478,447	2001–2011	4.7%	2010	35,607	2001–2010	37.9%

Table 4
Extracted weights based on AHP and fuzzy standardization.

Factors	Functions	Control points	Weights
Distance from roads	J-shaped	0–50 m highest suitability 50 m–1 km decreasing suitability >1 km no suitability	0.262
Distance from water bod./wetl.	Linear	0–50 m no suitability 50 m–12 km increasing suitability >12 km highest suitability	0.187
Distance from built-up areas	Linear	0 m highest suitability 0 m–6.5 km decreasing suitability >6.5 km no suitability	0.332
Slope	Sigmoid	0% highest suitability 0–15% decreasing suitability >15% no suitability	0.091
Land use categories	n.a.	n.a.	0.128

et al. (2010a) reported a slightly lower accuracy (71–83%). The extracted land use maps for 1973 to 2010 are illustrated in Fig. 3.

Multi-temporal change analysis of urban areas permits the quantification of growth over time. Overlaying the spatial footprints of two time stamps also permits the localization of urban expansion (Taubenböck et al., 2012). The visual interpretation of Fig. 3, in combination with Table 2 and Fig. 4, provides an overview of past development trends.

Several trends related to land use changes are apparent. Since 1973, a remarkable increase in built-up areas in both size and extent has occurred, while cropland and open spaces have decreased. Growth has occurred mostly in the northern and western areas surrounding the city, with both urban spread and density increasing. Spatially built-up areas have mostly expanded toward the surrounding areas along the main transportation axes. Although water bodies have exhibited some fluctuation over time (8–9%), green lands, wetlands, and open land and cropland have steadily decreased. Most notably, open land and cropland use decreased from 50% in 1973 to 30% in 2010, which, in comparison to

Table 5
Markov transition probabilities for the periods 1990–2001 and 2001–2010.

		Built-up areas	Water bodies	Wetlands	Forest and green space	Cropland and open land
1990–2001	Built-up areas	0.980	0.002	0.001	0.010	0.007
	Water bodies	0.034	0.954	0.010	0.002	0.000
	Wetlands	0.046	0.003	0.945	0.002	0.004
	Forest and green space	0.020	0.001	0.002	0.974	0.003
	Cropland and open land	0.112	0.001	0.001	0.002	0.884
2001–2010	Built-up areas	0.990	0.002	0.001	0.005	0.002
	Water bodies	0.061	0.930	0.008	0.001	0.000
	Wetlands	0.088	0.003	0.899	0.001	0.009
	Forest and green space	0.061	0.001	0.003	0.926	0.009
	Cropland and open land	0.252	0.001	0.001	0.003	0.743

all other land use categories, are the largest amounts of degradation observed.

The analysis of the urbanization process in megacities conducted by Basawaraja et al. (2011) and Bagan and Yamagata (2012) demonstrated that urban growth is directly linked to population changes. Table 3 compares the absolute and relative population change with urban growth for the selected time stamps.

During approximately the same time period, built-up areas increased by 367%, and the population increased by 109% from 1971 to 2010. Thus, a relationship exists between increasing population, demand for land, and the resulting increase in built-up areas. Note that in 2001, a 20% increase in population corresponded to an approximate 39.8% increase in built-up areas, whereas in 2011, this ratio changed dramatically (4.7% versus 37.9%). Over time, the proportion between population growth and land consumption changed considerably: in 2011, reduced population growth rates demanded many more built-up areas. This ratio difference is consistent with the claims of Chakrabarti (2001) that population growth and migration are key factors in turning Mumbai outward. To conduct a more holistic analysis, the city's growth was simulated using MC–CA, as described in the next section.

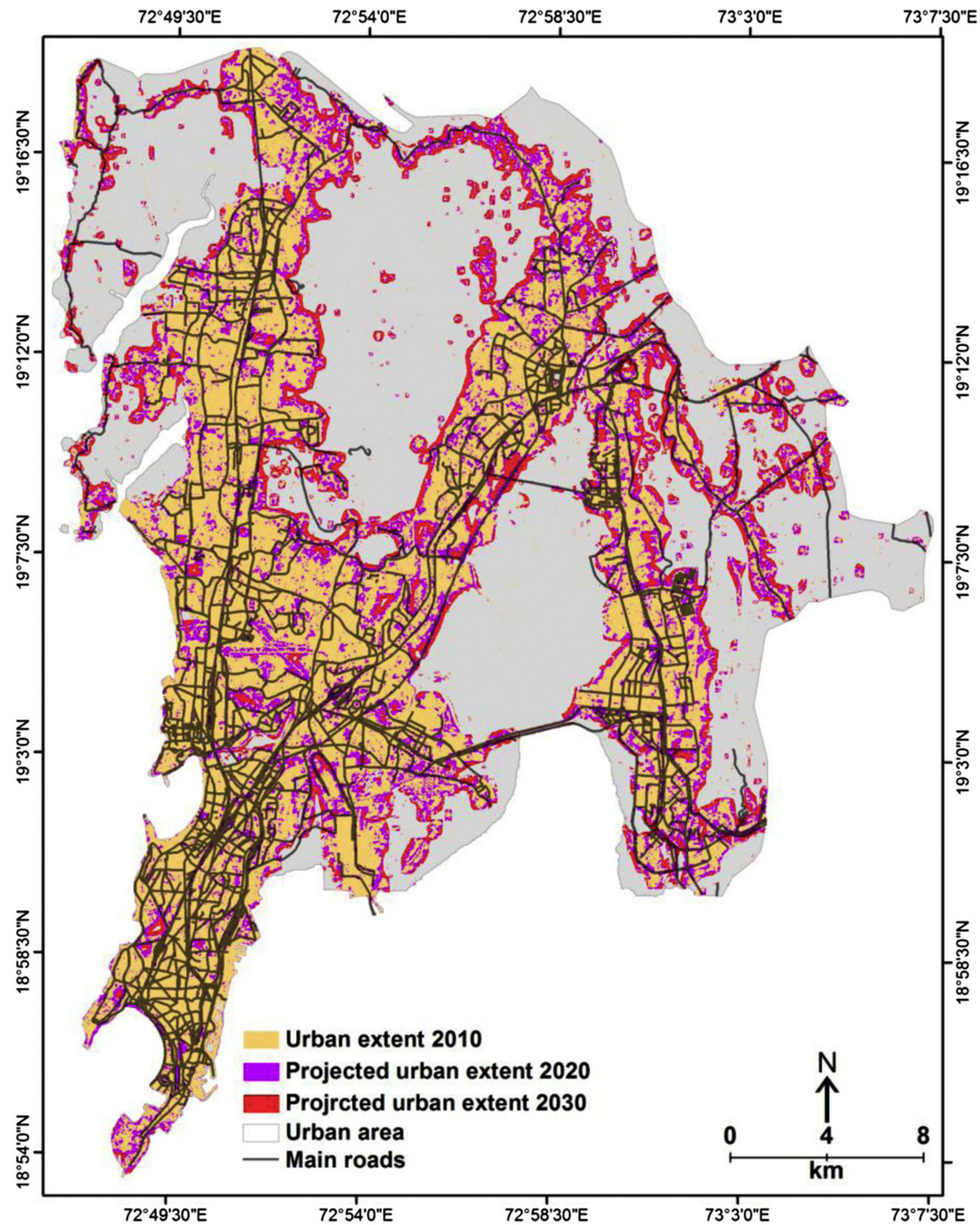

Fig. 5. Simulated urban extent of Mumbai for the years 2020 and 2030.

Simulating urban growth

Standardization and weighting of main factors

To evaluate the factors that shape urban expansion and effect land use transition probabilities, auxiliary variables, selected on the basis of preliminary studies (e.g., He et al., 2013; Jokar Arsanjani et al., 2013), were employed within an AHP framework. The relative importance of each criterion was determined by expert knowledge and on the basis of the published literature (e.g., Araya & Cabral, 2010). To verify the logical consistency of the selected weights, the consistency ratio was calculated. The value of 0.04, which is below the critical value of 0.1, confirmed the suitability of the defined weighting schema (Malczewski, 1999). The individual weights determined are listed in Table 4. Factors with higher weights are statistically more important.

Next, in agreement with Araya and Cabral (2010), the following three fuzzy standardization functions were used (Table 4): sigmoid, J-shaped, and linear functions with adjustable settings. For example, areas within 50 m of roads were considered most suitable. After this control point, suitability decreases up to 1 km, in accordance with the J-shaped membership function, but never reaches zero. Beyond a distance of 50 m from water bodies, which serves as a protective buffer, the degree of suitability increases with distance. We assumed that a linear increasing function would characterize this relation more robustly, compared to built-up areas, for which a linear decreasing function was applied to assess their effects on future changes. Agglomeration factors in urban economics (McDonald, 1997) show that future urban areas tend to be located closer to existing built-up sites. This is portrayed in the sustainability map as a linear decreasing function. In contrast, urban expansion occurs more often in flat areas than in hilly areas. Thus, we assume that areas with slopes less than 15% exhibit potential for urban growth, while beyond this threshold, sites are characterized unsuitable. This growth is modeled as a sigmoidal decreasing function in which suitability starts at zero and levels off at 15%. Finally, it must be noted that choosing the type of fuzzy membership function and corresponding control points is prone to subjectivity and could be biased by, for example, the researchers' knowledge. However, sensitivity analysis conducted by slightly varying the selected parameters showed no contradictory results. These potential change maps were considered in the MC–CA model described next.

Predicting future urban expansion

Based on land use conditions during the periods 1990–2001 and 2001–2010, transition potentials were computed using a Markovian process. The transition probability matrices of each land use type for both periods are given in Table 5. The diagonal elements represent probability values for self-replacement, referring to land use types that remain similar (Guan et al., 2011). In contrast, off-diagonal values indicate the probability of change from one land use category to another.

The results indicate that for 1990–2001 and 2001–2010, the built-up areas remained constant, whereas other land use classes were likely to turn into built-up areas. Table 5 shows that for both periods, cropland and open land possessed the highest likelihood of transforming into built-up areas. The likelihood was even greater in 2001–2010, a period during which the increased possibility of forest, green spaces, and wetlands changing to build-up areas precipitated more pressure on these areas. In general, all land use categories show a tendency to change into built-up areas, wherein the loss ranges between 1 and 25%.

Although probabilities of land use transition are provided on a per category basis, spatial distribution of occurrences within each land use class was lacking in the analysis. Hence, this intrinsic limitation of MC requires the integration of CA. For calibration purposes, CA first input the transition probabilities for the years 1990–2001 and the suitability map to project the previously known built-up areas for 2010. Following the example of Vaz et al. (2012), the CA allocated the cells by means of a 5×5 neighborhood matrix and one iteration per year. Careful model validation was conducted to assure accuracy and to ensure an applicable simulation that predicts effectively. Built-up areas were predicted for 2010 based on data from 1990 to 2001 and cross-compared with the actual amount of built-up areas. The kappa index of 83% shows an "almost perfect" agreement (Landis & Koch, 1977, p. 165) and confirms the accuracy of the model. Moreover, a descriptive summary statistic of the simulated built-up sites resulted in an area of 331 km^2, compared to the actual area of 355 km^2. Thus, the model slightly underpredicted the extent of built-up areas. Both accuracy assessments confirmed a high coincidence, which indicated that the chosen model parameters were suitable for forecasting. Accordingly, the model was refitted with similar parameter settings using the land use data from 2001 to 2010, the transition probabilities from 2001 to 2010, and the identical suitability map. The future patterns of urban expansion were then simulated for the years 2020 and 2030 (Fig. 5).

Finally, the spatial arrangement of the simulated built-up areas for 2020 and 2030 were tested by means of point pattern analyses (see Helbich, 2012). Quadrat count tests, using different quadrat sizes ranging from 500 to 5000 m, and spatial Kolmogorov–Smirnov tests (Diggle, 2003) are computed. Both tests assess the significance of spatial patterns, compared with the null hypothesis of complete spatial randomness of predicted build-up areas. With $p < 0.001$, neither the quadrat count nor the Kolmogorov–Smirnov test confirmed a spatially random distribution, which unequivocally suggests a significant clustered pattern of future built-up areas.

Conclusions

The urban agglomeration of Mumbai is one of the largest and fastest-growing urban regions in the world, and this growth has unprecedented effects on urban sprawl and population dynamics (Chakrabarti, 2001; United Nations, 2012). However, as yet, no research has explicitly addressed the simulation of future urban growth patterns of Mumbai. Given the prevailing high dynamism, spatiotemporal mapping conducted by Bhatta (2010a), Taubenböck et al. (2009, 2012), among others, requires tight coupling of remote sensing and urban growth modeling. Indeed, this is crucial if we are to develop a holistic understanding of booming and vital spatial developments in Mumbai. This approach ensures realistic and sustainable planning. In this context, our analysis contributes significantly to the literature by having demonstrated that urban growth models, by means of MC–CA, generate crucial information regarding urban futures in 2020 and 2030.

On a regional scale, the results show clear urban expansion and demonstrate that urban growth dynamics are strongly linked to population dynamics. The increase in urbanization is proportional to the generation of new infrastructure aimed at supporting population increases, which in turn causes additional fragmentation. Thus, the population plays an essential role in urban processes for Mumbai, a notion which is consistent with Bagan and Yamagata's (2012) megacity analysis of Tokyo, Japan. Moreover, strong evidence suggests that urban expansion will continue to occur in Mumbai throughout the next two decades. The temporal mapping of built-up areas and the simulations for the next two decades indicate that the projected urban expansion will coincide with the transportation networks and existing built-up areas, among other physical factors. The main swap in land use has occurred between built-up areas and open land and croplands, mainly because of a) the increasing economic value of these lands, b) the relative location of these lands nearby existing built-up boundaries, and c) the lack of regulatory protection that takes into account environmental considerations for areas such as wetlands and pastures.

Consistent with Taubenböck et al. (2012), complex local growth patterns were detected for the period between 1973 and 2010. More important, the MC–CA model predicted that this trend will continue through 2030, resulting in a mixture of different growth patterns. Apart from distinct axial developments driving urbanization along the main traffic routes through the surrounding northeastern and northwestern areas, this research shows that new urban nuclei will emerge in the next two decades and will be significantly clustered in space. This analysis supports predictions by Taubenböck et al. (2012), who anticipated the emergence of satellite towns. Our model also forecasts that between now and 2020, the independent settlement axes will merge and close the settlement ribbon around the Sanjay Gandhi National Park. Moreover, several notable smaller in-fill developments are predicted, most likely as a result of the limited amount of space within existing former built-up areas.

Our analysis demonstrates that the integration of GIS, remote sensing, and urban modeling offers an enhanced understanding of the futures and trends that megacities will face. It also provides important information for strategies directed at fostering sustainable regions. Future extensions of this research will be dedicated to the evaluation of different planning scenarios and policies on land use dynamics (e.g., He et al., 2013) and intensity analysis (e.g., Huang, Pontius, Li, & Thang, 2012). Moreover, to clarify whether the predicted urban growth patterns are specific to Mumbai, this approach must be empirically replicated and requires further comparative studies. In sum, these notable relevant findings should advise policy makers, urban planning, and land use management organizations. This will help them in preparation for the expansion of urban living and inform them of the extent of growth that can be expected, so that they can plan sustainable policy interventions (e.g., encouraging infill, imposing zoning regulations, establishing growth boundaries/limits) in the management of inevitable urbanization processes.

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