Urban Growth Evaluation: A New Approach Using Neighborhood Characteristics of Remotely Sensed Land Use Data

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Introduction

The physical and functional transformation of rural landscapes into urban forms is recognized as urban growth (Thapa and Murayama 2010). According to Clark (1982), urban growth is a spatial and demographic process that is characterized by a change in population distribution from a village to a town or city. Currently, rapid urban growth is a major worldwide trend, involving a variety of resources and environmental problems, such as habitat loss, species extinction, land-cover change, and alteration of hydrological systems (Hahs et al. 2009; Jain 2011). Driven by this trend, the understanding of urbanization has pushed to the forefront of environmental and development agendas (Mertes et al. 2015).

The typical spatial organization of individual urban areas is explained in von Thünen's (1826) bid-rent theory, Burgess's (1925) concentric zone model, Christaller's (1933) central place theory, and Hoyt's (1939) sector model. Although these studies have formed foundations for subsequent work, they are predominantly descriptive models that assume cities grow in a uniform or linear manner, and most do not contribute to the understanding of the spatiotemporal patterns of urban forms or growth (Dietzel et al. 2005). In addressing this limitation, various new and sophisticated methods have been developed and successfully applied for charac-

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terizing urban growth. Batty and Longley (1994) considered urban growth a cellular fractal stochastic process and modeled urban growth through the cellular automata method. Dietzel et al. (2005) suggested that the process of urban growth could be characterized through diffusion and coalescence. To connect the theory of diffusion and coalescence, three indicators of urban growth patterns—infill, extension, and leapfrog development—have also been identified (Estoque and Murayama 2015). In addition, in urban planning initiatives, the importance of the low, moderate, and high sublevels of each indicator has been highlighted.

By addressing the lack of more detailed urban growth identification, the remote sensing of urban landscapes has recently led to a number of new approaches to characterize urban growth on various spatial scales (Antrop 2004; Kantakumar et al. 2016; Xian and Crane 2005). Among them, ULU change analysis with a spatial metric has been widely applied (Aguilera et al. 2011; Estoque and Murayama 2011). Two major methods of land change analysis developed are spectrally based (image-to-image) and classification-based (map-to-map) change detections (Xian and Crane 2005). Furthermore, a large volume of successful research studies has employed both of these methods when characterizing ULU change in general and urban growth in particular (Dorning et al. 2015; Guindon et al. 2004; Mertes et al. 2015).

However, remote sensing applications for the urban growth evaluation still pose several limitations. Fundamentally, inconsistency in ULU definitions has created challenges in urban growth detection and evaluation (Taubenböck et al. 2012). Due to this inconsistency, remote sensing studies typically describe built environments as ULU, and the non-built environments as non-urban land use (Estoque and Murayama 2015; Liu et al. 2016; Su et al. 2011). However, some non-built land use dominates urban areas (e.g., parks and runways) in reality, and function as ULU. Thus, characterizing the urban area using only the built environments confound our understanding of urban growth (Mertes et al. 2015). In such a context, characterizing ULU classification based on their locational contexts or neighborhood interaction is vital and helps us to detect urban growth in a more realistic manner. Moreover, the neighborhood interaction of a surrounding area can be employed to elucidate low, moderate, and high levels of urban growth by determining major patterns.

In general, morphological spatial pattern analysis (MSPA) allows the integration of neighborhood interaction in defining ULU categories and helps to determine the levels of urban growth in a contextual manner (Ostapowicz et al. 2008; Vogt et al. 2007). Using MSPA, Vogt et al. (2007) developed a forestland classification (e.g., core, patch, perforated, and edge) based on forest and non-forest land categories. Angel et al. (2010) developed an urban land classification (urban, suburban, rural, fringe open space, exterior open space, and rural open space) based on built and non-built land categories. They have employed only binary land classification to classify the forest- related or urban- related land use categories. However, developing ULU classifications using binary land use or cover categories may be insufficient due to existence of a higher complexity of ULU (Jiao 2015; Zhou et al. 2015). In such a context, incorporation of ancillary data and multiple land categories with MSPA will provide more advancement in ULU classification and a clearer understanding of growth patterns.

In this study we present a new approach to recognize the spatial pattern of urban growth by integrating the neighborhood interactions of ULU categories. We called our approach the Urban Growth Evaluation Approach (UGEA); it was tested using a case study of the Colombo metropolitan area, Sri Lanka.

Concept of Neighborhood Interaction

Neighborhood interactions are an important component of many land use models connecting to the Tobler's (1970) first law of Geography ("Everything is related to everything else but near things are more related than distance things"). Cellular automata (CA) is commonly used to implement neighborhood interactions in land use models through Vin Neumann's adjacent four cells rule (Fig. 1a) or Moor's adjacent eight cells rule (Fig. 1b). In reality, a cell does not only influence the state of adjacent cells but also those located at a certain distance, although with less effect (Barreira-González et al. 2015). In this respect, distance decay function can be used to integrate neighborhood interaction to the cells (Fig. 1c) (Zhao and Murayama 2011).

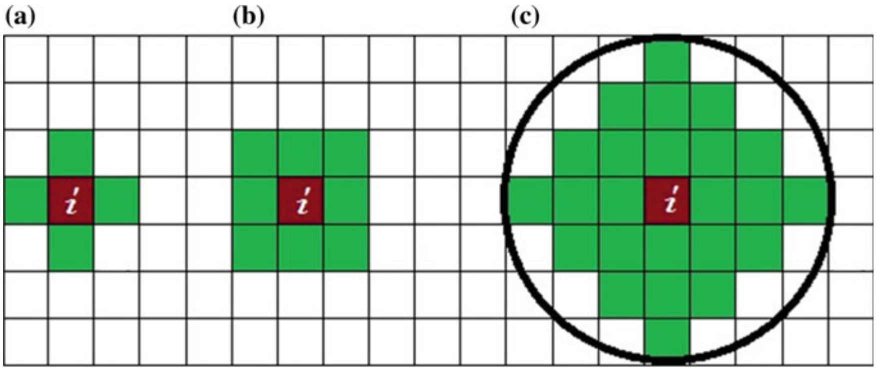

Fig. 1 **a** Van Neumann's concept (4 cells), **b** Moore's concept (8 cells), and **c** distance decay concept (i = processing cell)

Methods

Data

To test our UGEA, we acquired Landsat TM/ETM + images from the United State Geological Survey (USGS) website during the study area's wet seasons in 2001 and 2014. One Landsat scene (path 141 and row 55) covering the entire study area was collected for these two time points. The two images collected were Landsat-7 ETM + of 2001 and Landsat-8 OLI/TIRS of 2014. The Landsat-7 ETM + of 2001 and Landsat-8 OLI/TIRS images were Standard Terrain Correction (L1T) (Taubenböck et al. 2012) and cloud free. Therefore, geometric correction and atmospheric corrections were not preformed. In addition to Landsat images, Google Earth™ images and topographical maps (Department of Survey, Sri Lanka) were used for accuracy assessment and to delineate boundaries of some land use (i.e., protected areas, runways, etc.).

Determining Spatial Patterns of Urban Growth

Basically, UGEA turns the ULU change maps into an urban growth map through the several processes. All the processes can be summarized into three major steps (Fig. 2): (1) ULU mapping, (2) identification major spatial patterns of urban growth, and (3) development of sublevels of urban growth.

ULU Mapping

As the first step of UGEA, we developed a method to map ULU rationally. The ULU categories in the maps were mainly defined based on neighborhood interactions of the study area's land use categories.

We employed the hybrid classification (pixel-based and segment-based) to develop the initial study area's land use classification. With a method, first, we classified Landsat images using pixel-based (PB) classification techniques employing the maximum likelihood supervised classification approach available in the ENVI 5.2™ software package. This PB classification produced three land use categories: built (meaning built-up lands), non-built (meaning non-built up lands), and water (meaning bodies of water). Second, we classified the study area's land uses using segment-based (SB) classification. In SB classification, Landsat images were segmented using the ENVI 5.2 software package and produced two land uses: protected areas, and urban open space (runways, playgrounds, and parks), employing region merging techniques of SB classification technique. The SB classification method is the most appropriate classification method to classify land

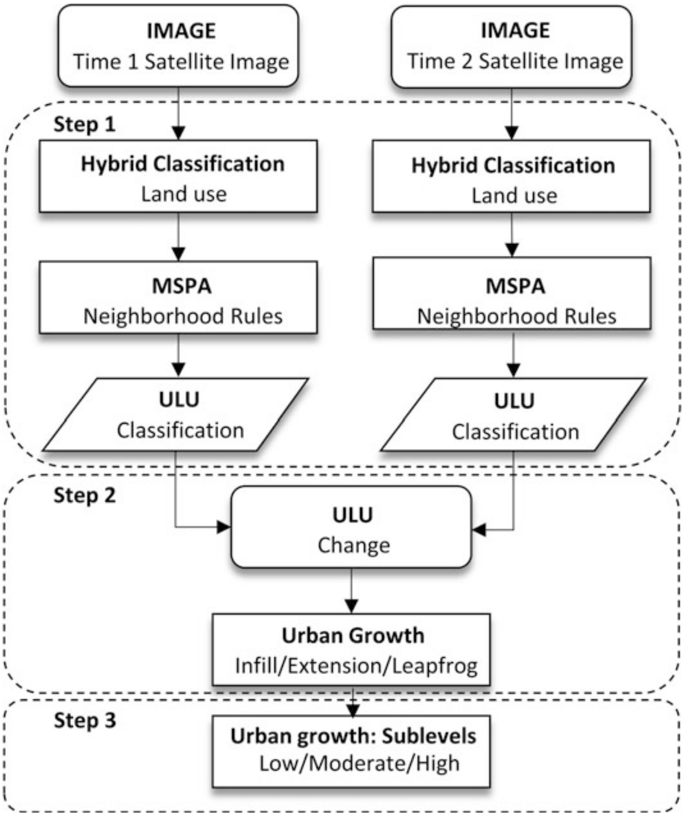

Fig. 2 Flowchart showing all the steps in UGEA

use categories having specific boundaries or edges such as parks, protected areas etc. (Blaschke 2010). Third, the results of PB classification and the SB classification were integrated using the raster algebra tool in the ArcGIS™ software package. The final output of this hybrid classification contained five land use categories: built, non-built, protected areas, urban open spaces (parks, playgrounds, and runways), and water. It is agreed that a higher level of accuracy can be maintained with the hybrid land use classification method than individual PB or SB classification methods (Li et al. 2013). The accuracy of land use classification was checked using 300 samples at each time points (2001 and 2014) through careful and rigorous visual inspection. Google Earth images were used as reference data for accuracy assessment and the overall accuracy was (Congalton 1991) 90.33, and 92.66% for 2001, and 2014 respectively in this hybrid classification method.

Neighborhood interaction rules were processed using MSPA to convert the study area's land use into ULU mapping. To process the neighborhood rules, we first defined the active land use categories and inactive land use categories in the study area. The active land use category means the land use categories that influence ULU

Table 1 Neighborhood interaction rules of ULU categories

ULU categories	Description of neighborhood interaction rule
Urban dense	50–100% built-up pixels in a 1-km^2 area of neighborhood: Buffer with 564 m map unit (18 pixels) distance from built pixel was employed to determine a 1-km^2 area
Urban sparse	10–50% built-up pixels in a 1-km^2 area of neighborhood: Buffer with 564 meters map unit (18 pixels) distance from built pixel was employed to determine a 1-km^2 area
Urban open space	Non-built land within a 100-m distance from urban area: Buffer with 100 meters map units (3 pixels) distance from urban built was employed to determine a 1-km^2 area
Captured urban open space	Patches of non-built, less than 2 km^2, completely surrounded by urbanized area (included urban dense, urban sparse, and urban open space)
Urban fringe	100-m (3 pixels) distance edge in between urbanized (included urban dense, urban sparse, and urban open space) and non-urban area (included non-urban built and non-urban open space)
Non-urban built	0–10% built up pixels in a 1-km^2 area: buffer with 564 m map unit (18 pixels) distance from built pixel was employed to determine a 1-km^2 area
Non-urban open space	All other land use

Note All the measures are computed based on raster data 30 m × 30 m pixels

classification as a neighborhood. Inactive land use means the land use categories that do not influence ULU classification as a neighborhood. Here, we considered built and non-built land categories as active land use categories and protected areas, urban open space (parks, playgrounds), and water as inactive land use categories. Second, the neighborhood interaction rules (Table 1) were processed and defined ULU categories. The neighborhood rules were performed for each pixel of land use using the urban growth analysis (UGA) tool, developed by the Center for Landuse Education and Research Institute (CLER), and the ArcGIS focal analysis tool. As a result of this process, seven ULU categories (urban dense, urban sparse, urban open space, captured urban open space, urban fringe and non-urban area) were classified.

Figure 3 illustrates how the neighborhood interaction rules are processed on a cell space.

Later, these seven ULU were integrated with protected areas, urban open spaces, and water, which are classified in hybrid classification. The protected area was converted into non-urban open space and the final ULU map was contained eight categories: urban dense, urban sparse, urban open space, captured urban open space, urban fringe, non-urban built, non-urban open space, and water. In the present study, we produced two ULU maps with eight categories for 2001 and 2014 to detect the spatial patterns of urban growth.

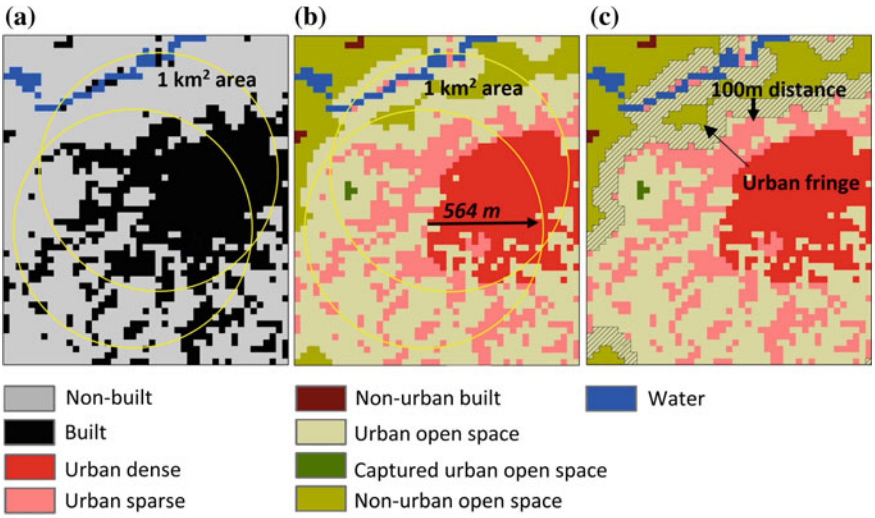

Fig. 3 The neighborhood interaction area: **a** and **b** the percentage of built pixels is calculated within a 1 km^2 area, and **c** distance from non-urban areas is determined

Identification of Major Spatial Pattern of Urban Growth

To spatially characterize urban growth, we distinguished the three major spatial patterns of urban growth—infill, extension, and leapfrog development. The ULU transition from the initial time point and the final time point were used to detect these growth patterns (Table 2).

Briefly, each urban growth pattern contains the following characteristics: (1) infill, characterized by new urban development that occurs in an already

Table 2 ULU changes used to characterize the three major urban growth patterns

Urban growth pattern	Change from	Change to
Infill	Urban open space	Urban dense
	Urban open space	Urban sparse
	Captured urban open space	Urban dense
	Captured urban open space	Urban sparse
Leapfrog	Non-urban built	Urban dense
	Non-urban built	Urban sparse
	Non-urban open space	Urban dense
	Non-urban open space	Urban sparse
Extension	Any above transition occurs in the urban fringe area and connected new development to the extension	

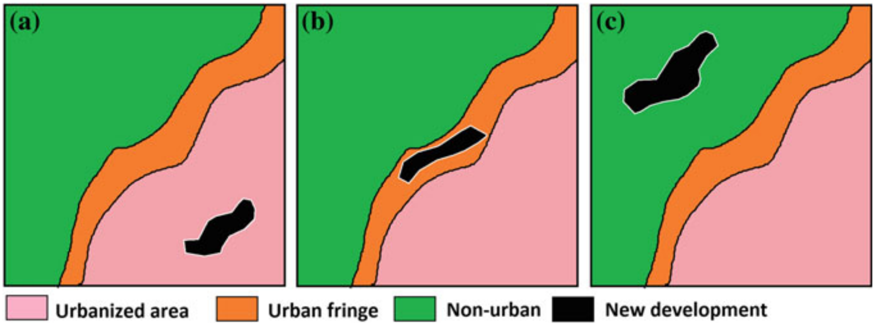

Fig. 4 Locational characteristics of each development pattern: **a** infill, **b** extension, and **c** leapfrog development

urbanized area (Fig. 4a); (2) extension, characterized by new urban development which occurs in the urban fringe area and connects it to new development, (Fig. 4b); (3) leapfrog development, characterized by new development that occurs in a non-urban area (Fig. 4c).

Concept of Urban Growth Sublevels

We further separated the major patterns of urban growth into three sublevels: low level, moderate level, and high level. These sublevels were determined based on the nature of the development in the surrounding area or neighborhood interaction. In doing so, the nature of urban dense land category and urban sparse land category was considered within a 1-km^2 area (same as ULU classification). A buffer with 564 m of distance was employed to delineate the area of neighborhood interaction (a 1-km2 area). Figure 4 illustrates examples for locational characteristics of each sublevel separation.

Figure 5a illustrates the urban growth occurring in an area where the surrounding area is characterized by a low level of development. Figure 5b illustrates urban growth occurring in an area where the surrounding area is characterized by a moderate level of development. Figure 5c illustrates urban growth occurring in an area where the surrounding area is characterized by a high level of development.

Sublevel Separation Process

We employed the Map algebra tool in ArcGIS to calculate the proportion of urban dense area and urban sparse area as a percent of the total land area (except water) within a 1-km^2 area. In this processing, two main raster layers were used. Figure 6

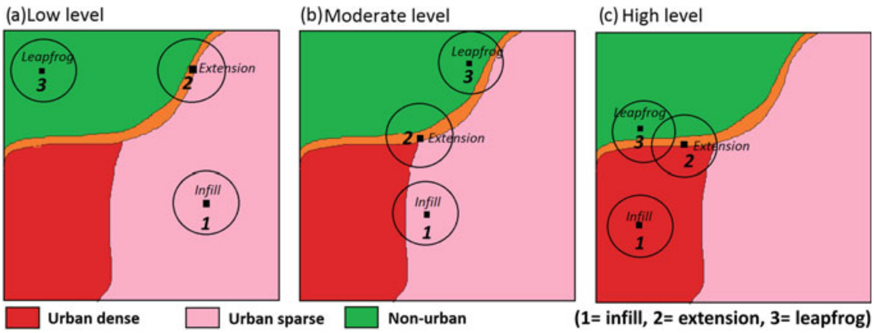

Fig. 5 The sublevels of urban growth patterns

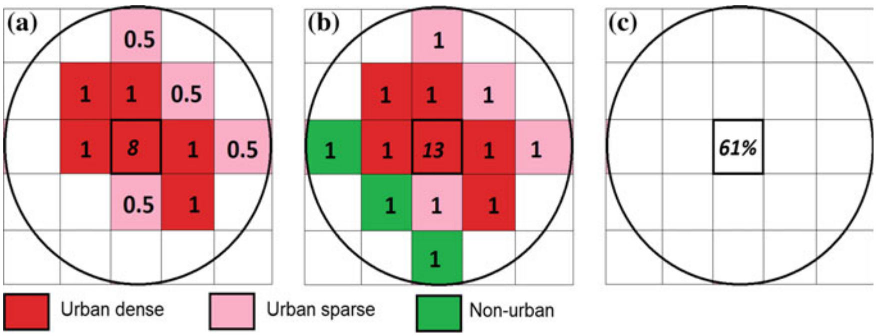

Fig. 6 Calibrated values of land use: **a** first layer containing only urban dense and urban sparse areas, **b** second layer containing all land uses (except water), and **c** resulting layer with percentage values

illustrates a simplified example the calibration process used for sublevel separation. The first layer containing only urban dense and urban sparse calibrated was calibrated (urban dense value = 1, and urban sparse = 0.5). The second layers contain ULU categories, which were calibrated with ULU value = 1, except water (water = no data). The percentage of the first layer was calculated according to the presence of the second layer. This calculation is simply explained in Eq. 1.

$$Sl = \frac{\sum (Dp + Sp)}{UL} \times 100 \tag{1}$$

where Sl is the percentage of the development level of the surrounding area, Dp is the total value of urban dense pixels in the first layer, Sp is the total value of urban sparse pixels in the first layer, and UL is the total value of ULU categories in the second layer.

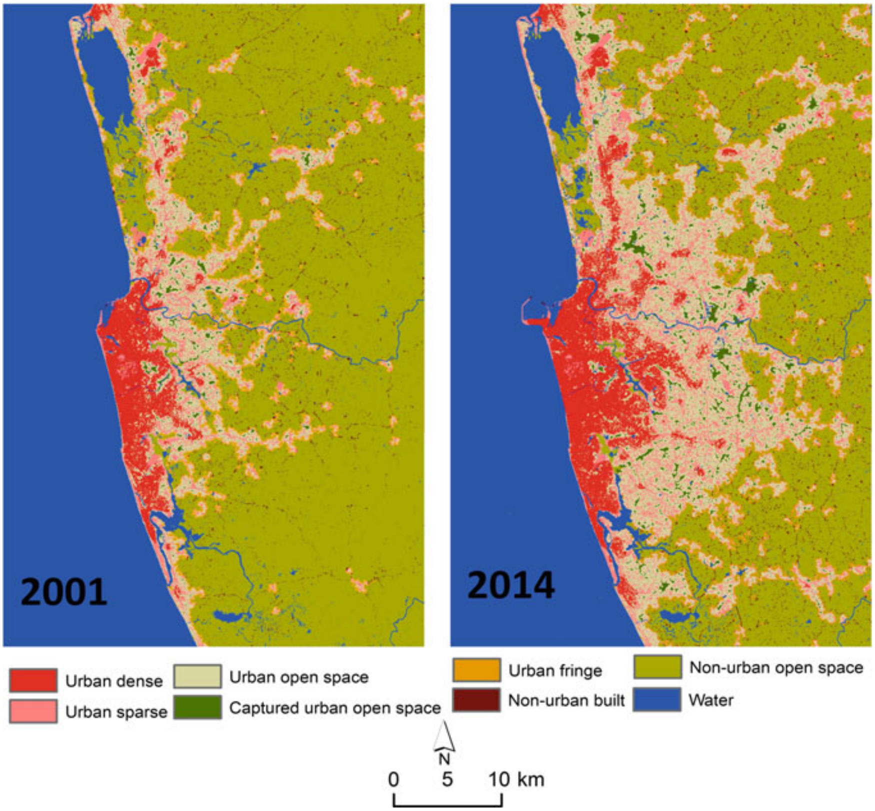

Fig. 7 ULU maps for 2001 and 2014

Depending on the produced percentage of development for each pixel, the main patterns of urban growth (infill, extension, and leapfrog development) were subdivided into low level (0–20%), moderate level (20–70%), and high level (70–100%).

Results

Figure 7 presents the results of ULU mapping for 2001 and 2014.

The major spatial patterns of urban growth, derived from the ULU change, are presented in Fig. 8a, and the sublevels of each pattern are presented in Fig. 8b.

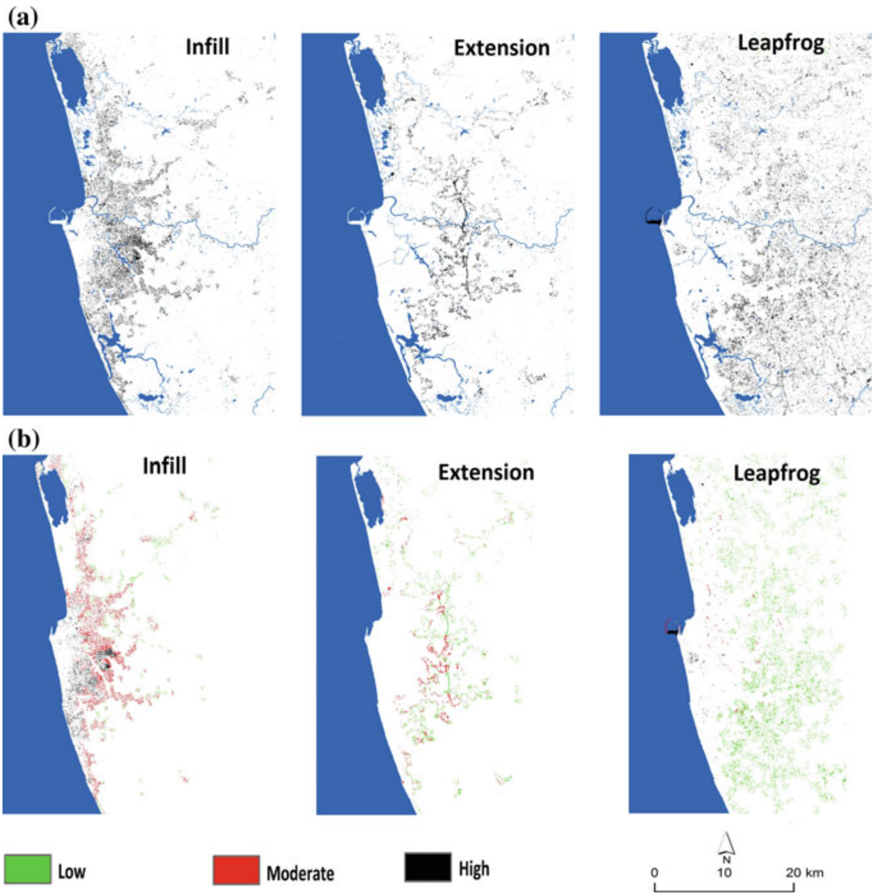

Fig. 8 The urban growth patterns: **a** major patterns, and **b** sublevels

Discussion

UGEA as a Geographic Approach

Fundamentally, an approach contains a set of methods and techniques with clear starting points, transition points, and end points. Geographic approaches allow us to understand the world by organizing, analyzing, and modeling various geographic data (Dangermond 2007).

McHarg (1969) articulated the philosophical context of the geographic approach for managing human activities within natural and cultural landscapes. His approach created a fundamental factor for geographers to analyze our world. The geographic approach consists of five steps (Fig. 9).

Fig. 9 Five steps of the geographic approach

The first step formulates the question from a location-based perspective. In present study, as the research question, we ask, "What are the spatial patterns of urban growth?" This question establishes the urban environment as the geographic context as we attempt to understand the spatial patterns of urban growth. Analyses integrating spatial aspects lead to a greater fundamental understanding of the dynamic process involved and thereby aid in the development of actual solutions (Ding and Elmore 2015).

The second step determines the necessary data that should be acquired by the analysis. We deal with remotely sensed big data in a data-poor environment. Satellite images are the main data and are to produce ULU maps by image processing. Satellite image processing comprises four basic operations: (1) image restoration, (2) image enhancement, (3) image classification, and (4) image transformation (Thompson et al. 2002). In the present study, we mainly conducted geometric corrections and visual enhancement for Landsat images, and image processing with MSPA in relation to this step.

The third step examines the acquired data to understand whether the prepared data is appropriate for achieving the objectives and answering the research questions. It is necessary to visually inspect it and understand how the data is organized. Here, we visually inspected and assessed the accuracy of our outputs.

The fourth step performs the data analysis. After examining the data, here we analyzed the spatiotemporal pattern of urban growth and separated it into sublevel based on its neighborhood interaction. Furthermore, the difference in urban growth was analyzed based on time intervals.

The fifth step presents the results visually. Visual presentation through maps, tables, and charts is a common method with the geographic approach. The International Cartographic Association's research agenda identified four visualization goals: exploration, analysis, synthesis, and presentation (MacEachren 1994). In this study, we present our ULU classification results and urban growth pattern visually using geospatial techniques.

Contributions of the UGEA

The problem of identifying a more realistic means of urban space representation and urban growth identification appears to have been almost solved by high resolution remote sensing imagers in the big data era (Barreira-González et al. 2015). However, the practical applications of high resolution satellite images to characterize the urban growth of large urban areas such as metropolitan areas (particularly in developing countries) have been limited by the cost and availability of high resolution satellite imagery. Similarly, the lack of socioeconomic data in developing countries has also limited the urban growth evaluation.

There has been rapid and vital growth of urban areas in developing countries over the last two decades, and drastic urban growth is predicted for these regions in the future (Cohen 2006; Seto and Fragkias 2005). Thus, the main purpose of the present study was to develop a new approach to characterize the spatiotemporal patterns of urban growth with minimal data input and complexity for widespread use and applications. The introduced UGEA can be performed with Landsat imagery and widely available ancillary data (i.e., Google Earth images, and topographical maps). Because of this advantage, the application of this approach in developing countries can be assured.

As previously mentioned, earlier approaches, which employed limited sources, mostly used the built-up areas as urban areas, and urban growth was characterized using the land use change from non-built to built. Our proposed UGEA uses the advantages of the neighborhood interaction concept to overcome the narrow view of previous studies, and introduced a wide range of urban land use categories and urban growth patterns. In this sense, the UGEA enables a conceptual and practical solution to characterize urban areas in a data-poor context.

Although the neighborhood interaction concept with remotely sensed land use may be a good option, it also presents some limitations. An urban area not only depends on the neighborhood land use types, but also on socioeconomic and political factors, which are highly influential in the urban areas (Kantakumar et al. 2016). Thus, it is necessary to integrate these factors with remotely sensed data to define an urban area. Furthermore, this study remained “blind to pattern” (Longley 2002) and it requires a knowledge of processes and driving forces to characterize urban areas in a more comprehensive manner.

Technically, we analyzed urban growth patterns in the study area using ArcGIS focal analysis and the UGA tool. The processing of this big data with neighborhood interaction rules in the ArcGIS environment is very time consuming and costly; therefore the use of Python code, a one of the widespread programming languages in geospatial analysis and data management may be, an appropriate solution.

Conclusions

The new approach introduced in this study—UGEA—addresses two key urban application needs. As a key to urban growth evaluation, the UGEA initially develops land use classification using the neighborhood interaction rules of land use. In general, ULU classification is associated with several difficulties related to medium resolution satellite imagery like Landsat due to the higher level of complexity and heterogeneity of urban areas. Thus, the classification of ULU categories from Landsat requires knowledge of the larger scale of the spatial context. The concept of the neighborhood that is available in geospatial analysis enabled a solution to incorporate a large-scale spatial context to our ULU mapping.

Subsequently, urban growth was detected using three patterns (infill, extension, and leapfrog development) and separated into different levels depending on the locational context. The incorporation of location context to the sublevel classification of urban growth is a new idea introduced in this study; it can be further developed in the future. Here, we used only the distribution of urban dense and urban sparse land categories to separate the sublevels, but the incorporation of additional urban features (i.e., industries, administrative, and services) can lead to more sophisticated sublevel classification.

This approach is more applicable to comparative urban studies than to individual case studies. Comparative analysis would help to elucidate the urbanization process of each city separately and compare the difference in urbanization processes. In such a context, the development of a GIS-based tool to conveniently run all the steps of UGEA would be useful in future research activities.

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