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Land use and land cover change detection and prediction in Bhutan's high altitude city of Thimphu, using cellular automata and Markov chain

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ABSTRACT

Rapid urbanization is changing landscapes often resulting in the degradation of ecosystem services and quality of urban life. Remote sensing and GIS tools can provide valuable information to deepen our understanding of the dynamics of these changes to better plan and build sustainable cities for the future. Using remote sensing data, socio-economic data, and field observations, we simulated spatiotemporal dynamics of land use and land cover changes in the city of Thimphu. Simulation results reveal that the landscape of Thimphu city has changed considerably during the study period and the change trend is predicted to continue into 2050. The study observed a significant increase (12.77%) in built-up area from 2002 (52.88%) to 2018 (65.5%), followed by a slight increase in the cover of bare ground. On the contrary, forest cover declined drastically (15.25%) followed by agriculture (1.01%). Rapid population growth triggered by rural urban migration coupled with hasty socio-economic development post democracy are the main drivers of these changes. These changes have fragmentated forest cover, increased soil/gully erosion, surface runoff, and storm induced floods of storm and sanitation drains, thereby impinging on the overall quality of life in the city. Under the business as usual scenario, prediction analysis for the year 2050 show that built up area will consume almost all of the city area (73.21%) with forest significantly reduced to patches making up only about 16% of the city. These findings beg for an urgent need to implement effective planning specially to protect the existing forest and water resources from further degradation.

Introduction

Global cities, which are the engines of economic development (Sherbinin, et al., 2007) with large populations, are most vulnerable to the impacts of land use and land cover (LULC) changes. The LULC change is a driver of global environmental change such as emission of greenhouse gases (MEA, 2005), habitat loss/fragmentation and biodiversity loss (Lambin, et al., 2000, Sala, et al., 2000), and reduce the quality of human wellbeing (Lambin, 1997; Boissiere, et al., 2009). Rapid increase in human population and associated economic development further exacerbates the rate of these changes especially in fast growing urban areas (Liping, et al., 2018) threatening their sustainable growth. According to the figures from the UN (2016), over 54.4% of the world population in 2016 lived in cities and it is projected to increase to 60% by 2030 exerting extra pressure on urban resources. This increase is progressing at a higher rate in the developing countries where cities are growing thereby rapidly changing urban landscapes. Such rapid growth in the absence of adequate plan and infrastructure expedites LULC changes which are associated with degrading ecosystem services and human well-being (Mallupattu and Sreennivasula, 2013; Kanal, et al., 2019; Mishra, et al., 2019. Generally, cities in developing nations are characterized by poor infrastructural plans, high immigration rates, growing squatter settlements, etc. This demand addressing unique challenges and opportunities for urban adaptation and mitigation responses and for mainstreaming them into urban development plans.

Under such scenarios, studies using high resolution images and GIS can provide scientifically reliable information for planning environmental and economic development programs that are sensitive to achieving social and environmental goals (Weng, 2001; Rogan and Chen, 2004; Suresh, et al., 2011; Dutta, 2012; Rimal, et al. 2018). For instance, Addo (2010) asserted that remote sensing and GIS tools for mapping LULC changes can offer critical policy recommendations for sustainable land management. A review of global literature on the use of remote sensing and GIS for detecting and predicting LULC changes revealed that a significant amount research (Kalnay and Cai, 2003; Turner, et al., 2007; Huang, et al., 2008; Islam and Ahmed, 2011; Hansen, et al., 2013; Taubenbock, et al., 2014; Hassan and Nazem, 2015; Appiah, et al., 2015;

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Liping, et al., 2018; Wang, et al., 2020) using remote sensing and GIS to model LULC dynamics has accumulated. Geospatial modelling analysis lies at the heart of these studies (Rogan and Chen, 2004; Coppin, et al., 2004). These models attempt to detect where the change occurred or will potentially occur (Veldkamp and Lambin, 2001). Most of these models use historical land use data to assess the past land transformation and transition, which in combination with environmental variables can predict future land use scenarios (Eastman, 2009). Predicted land use changes exhibiting major modifications and alternations can help land use planners, resource managers, and conservation officers in promoting sustainable management and mitigating negative impacts. Consequently, detecting and predicting LULC changes have become an important consideration in a variety of fields including, modelling rural and urban plans (Theobald and Hobbs, 1998; Kumar, et al., 2013), identifying biodiversity hotspot landscapes (Wang, et al., 2020) for advancing conservation efforts, studying dynamics of desertification, etc.

These studies have generated highly credible information on the state of land use changes and their drivers, which can inform better decision making for sustainable planning of cities (Lu, et al., 2004). Therefore, an accurate geo-spatial modelling of urbanization to underpin the fundamentals of location, characteristics, and consequences of urban expansion is a pre-requisite for sustainable development of cities. Geospatial analysis use various statistical and rule based modelling approaches for detecting and predicting land use changes (Overmars, et al., 2003; Lu, et al., 2004). Commonly used models in estimating land use changes are; statistical models (Hyandye, 2015), evolutionary models (Aitkenhead and Alders, 2009), cellular models (Singh, et al., 2015), Markov models (Yang, et al., 2012), hybrid models (Subedi, et al., 2013), expert system models (Stefanov, et al., 2001), and multi-agent models (Ralha, et al., 2013). Of these the most popularly used are the cellular and Markov chain analysis and their hybrid model called the CA-Markov model (Zhao and Peng, 2012; Sohl and Claggett, 2013). The Markov chain analysis is a random stochastic modeling approach that is discrete in both time and state. The model defines the LULC transition from one time (t_1) to the next (t_2) to predict future change at a time (Sherbinin, et al., 2007) to project probabilities of land use changes for the future. This is achieved by using the known probabilities from the past changes to predict future changes. This is based on the assumption that the probability of a system being in a certain state at certain time can be determined if its state at an earlier time is known (Lambin, 1997). While Markov analysis has been used to simulate and predict land use changes (Muller and Middleton, 1994), it is best used for short term projections (Lambin, 1997; Sinha and Kumar, 2013) as its analysis is not spatially explicit (Sklar and Costanza, 1991). In addition, it does not consider spatial information allocation within each class and the probabilities of change between landscape states are not constant. Hence, it can offer the right magnitude, but not the right direction of change. This short coming is mitigated by creating a superior CA-Markov model that combine the Markov model with a more dynamic and empirical cellular automata model (Subedi, et al., 2013). Cellular automata is a bottom up dynamic model that incorporates the spatial dimension and thus adds modeling direction (Subedi, et al., 2013). Together CA–Markov model has the ability to stimulate and predict spatial transitions in complex land use systems and has outperformed regression-based models (Theobald and Hobbs, 1998). Thus CA-Markov model is widely used by scholars to understand urban expansion and landscape dynamics globally (Araya and Cabral, 2010; Islam and Ahmed, 2011; Guan, et al., 2011; Sohl and Claggett, 2013; Kityuttachai, et al., 2013; Dutta, 2012; Puertas, et al., 2014; Hassan and Nazem, 2015; Han, et al., 2015; Li, et al., 2016; Keshtkar, et al., 2017; Rimal, et al., 2017). Given its robustness and popularity, the present study used CA-Markov analysis to carry out the geo-spatial analysis of Bhutan's Thimphu city.

The Kingdom of Bhutan is located in the rugged landscape of the eastern Himalayas between 88° 54' and 92° 10' E and 26° 40' and 28° 15' N (MoWHS, 2008; Banerjee and Bandopadhyay, 2016; Wangda, 2017). Rapid changes in elevation from 100 amsl (above mean sea level) in the south to over 7000 m amsl are associated with varying climate, ecological zones, high biological diversity, and diverse livelihood systems (Wang et al., 2019b). Like many other mountainous countries, despite the cautious development Bhutan continues to face multiple threats to its ecological and livelihood systems including from rapid urbanization and LULC changes (Yangchen, et al., 2015; Wang et al., 2019a). Rapid population growth triggered by high immigration (14.5%) looking for better opportunities and basic facilities (Walcot, 2011) have resulted in unprecedented LULC in Bhutan's cities. Recent transition to democracy in 2008 ushered in expedited socio-economic development that is adversely changing landscapes especially in urban cores. For instance a study by Yangchen, et al. (2015) in their analysis of Bhutan's LULC change from 2000-2013, reported that the built up area has increased from 6% in 2006 (pre-democratic Bhutan) to 14% in a matter of 7 years (post democracy). In addition, Bruggeman, et al. (2016) attributed Bhutan's recent forest cover loss to the recent socio-economic and political changes. Existing literature (NSSC and PPD, 2011; Hansen, et al., 2013; Gilani, et al., 2015; Yangchen, et al., 2015; Bruggeman, et al., 2016; Sharma, et al., 2016; FRMD, 2017; Wangda, 2017) collectively confirm that the country has experienced rapid and increasingly pronounced LULC changes over the last 40 years. The studies also attributed major land use changes to a suite of drivers including expansion of urban cores.

The impact of LULC changes are more serious in the cities than other areas mainly due to pressures from population, developmental programs, and rate of urbanization (Gilani, et al., 2015). Such trends, if not mitigated could lead to irreversible changes in landscapes with serious negative impacts on human wellbeing (settlement, livelihoods, health, etc), as well as natural resources and ecosystem services (MRC, 2010). Yet, no study has attempted to simulate the dynamics of LULC changes for Bhutan's rapidly growing cities, let alone predict future scenarios. This situation demands a deepened understanding of the LULC dynamics to identify technical and policy options that can guide planners and policy makers to build more sustainable cities in Bhutan. As the capital city, Thimphu is the center of socio-economic and political activities in the country and presents itself as a typical representative of other cities in Bhutan. The city is located between 2,347 m amsl to 2,438 m amsl (Walcott, 2011) and like many others, this small mountain city is experiencing rapid urbanization that is changing its landscape and degrading its social and ecological resilience. Rapid population growth (triggered by high immigration (14.5%) and the government's directive for the city to expand and build infrastructures topped with growing tourist numbers, and expat workers), and associated rise in vehicle numbers are exerting increasing the rate of land use changes. Consequently, the city is grappling with classic problems of growing slums, ecosystem degradation, insufficient basic facilities including drinking water, and increasing frequency of disasters such as landslides, forest fires, flash floods, etc. (Wang et al., 2019a). Despite the growing challenges faced by the city, its planners, and the inhabitants, no studies have attempted to understand the dynamics of LULC changes and their drivers. Hence this study represents the first attempt to simulate LULC in Thimphu city using remote sensing and GIS techniques.

Methodology

Study area

Thimphu city, the capital of Bhutan is the crucible of socio-economic, political, and environmental development in the country. Administratively, the city is composed of central core, southern extension, and northern extension. Geographically, the city is located at 27° 29'N latitude and 89° 36'E longitude between an elevation of about 2347–2438 m amsl (Walcott, 2011) (Fig. 1). With an area of 26.2 km^2 (Wang et al., 2019a), the city stretches for about 15 km from Dechencholing in the north to Babesa in the South along the narrow banks of the Wang chhu river ("chhu" means river in Bhutanese language") which drains south

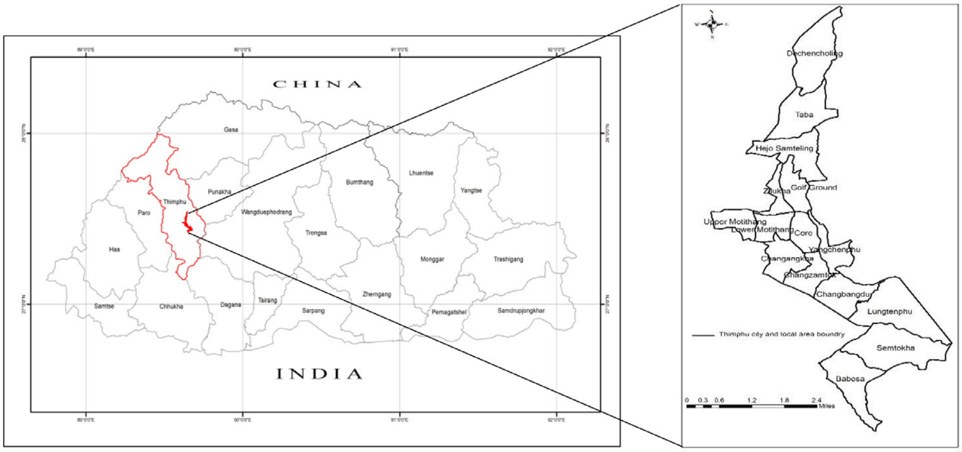

Fig. 1. Map of study area showing local areas.

into India (MoWHS, 2008). Except for this narrow valley leading to the south, the city is surrounded by mountains rising over 2,648m on all sides. The mountains are mostly covered in forests composed of blue pine, hemlock, spruce, oak, transitioning into alpine meadows, which forms important watersheds that drains into river Wang chhu. Like the rest of the country, Thimphu city experiences 4 seasons. Winter temperatures range from freezing at high elevations (at night) to 12.3°C during the day, while summers are warmer with temperatures ranging from 21°C (night) to 32°C during the day (Walcott, 2011). The city on the average receives about 813 mm of rainfall annually with much of the rainfall happening during monsoon period from June through September (MoWHS, 2008). Combination of elevational gradient topped with different types of forests has endowed the city and its periphery with diverse flora and fauna (Wang et al., 2019a). Riparian vegetation, marshland vegetation, and recreational parks are the dominant types of vegetation within the city and its periphery. A number of ornamental plants and trees such as willow, poplar, juniper, beech, and hibiscus have also been planted within the city.

With over 15.75% (114,551) of Bhutan's entire population (727,145) living in Thimphu, it is the most populated of all the cities of Bhutan (NSB, 2017). This represents a rapid population growth of about 62.04% from 2002 (43,479) excluding armed forces and monk body (Norbu, 2020 unpublished). Rural urban migration at 14.53% (Walcott, 2011) is primarily responsible for rapid population growth which currently stands at 3.7%. According to the statics from the National Statistics Bureau (2017), 54% of Thimphu city's population is composed of people who have immigrated from rural areas. This population is further inflated by a steadily growing population of expat workers and tourists (TCB, 2016). Rapidly growing urban population coupled with urban expansion and development is stretching the ecological and infrastructural carrying capacity of the city. Already, the city is facing problems of inadequate infrastructure, squatter settlements, traffic congestion, flooding along riverbed (triggered by rainstorms, glacial lake outburst floods), and low-lying pockets in the city due to inadequate storm and sewage drains, as well as landslides. International Environment Development (IIED) has classified Thimphu city as one of the 15 most vulnerable cities in the world (IIED, 2009).

Land policy and regime changes

Historically, Thimphu city started in 1961 with some 25 shops or so which currently falls within the central core of the city. Prior to this, the area was occupied by terraced agricultural fields and some 13 villages. Planned development for Thimphu started in 1985 with the establishment of National Urban Development Commission. Since then, two major policy interventions have expediated the growth of the city thereby changing its LULC:

Table 1
Characteristics of data collected.

Sensor	Month/Day/Year	Resolution	Path /Row
Landsat 7 ETM+	11/07/2002_Thimphu	30 m	138 / 41
Landsat 8 OLI	11/27/2018_Thimphu	30 m	138 / 41

Source: (Source: http://glovis.usgs.gov)

(i) *Approval of city extension*: Government approval of the comprehensive structural plan for Thimphu city in 2002, approved the expansion of the core area towards the south and north (Norbu, 2020 unpublished). This expansion rapidly replaced traditional buildings, agricultural fields, forests, and wetlands by buildings, roads, and other artificial infrastructures.
(ii) *Transition to democracy in 2008:* Bhutan transition to democracy in 2008, resulted in policy changes that favored rapid socio-economic development to partly impress voters. This move expediated the construction of public infrastructures such as roads, parking lots, recreational spaces, and other basic facilities in the city. In addition, changes in fiscal policies allowed easy access to housing loans thereby sparking a construction boom in the city. These developments exacerbated the rate of LULC mainly from agriculture and forests to built. The construction projects recruited expat workers from India, who together with already existing population and tourists also contribute to the LULC in the city.

Data acquisitions and preparation

Methodological framework of the simulation has been illustrated in Fig. 2. Spatial and socio-economic data further validated by the first author's expert experience and field observation in the study area were used to simulate the LULC changes in the study area. Landsat-7 Thematic Mapper (TM) and Landsat-8 Operational Land Imager (OLI) images at a resolution of 30 m were acquired for the years 2002 and 2018 respectively, from the United States Geological Survey (USGS) Center for Earth Resources Observation and Science (EROS) found at http://glovis.usgs.gov/. The specifications of the satellite data acquired for change analysis are given in Table 1. Post monsoonal data were used as these periods represent clear skies with least clouds.

These data sets were imported into TerrSet satellite image processing software to create a false color composite. Other geospatial data collected from Thimphu city office include, digital elevation model (DEM 30 m resolution), administrative boundaries, and infrastructure data such as road networks, drainage networks, water bodies, buildings, and other important establishments in the city. Additionally, field consultations with select communities, experts, and planners from the city office

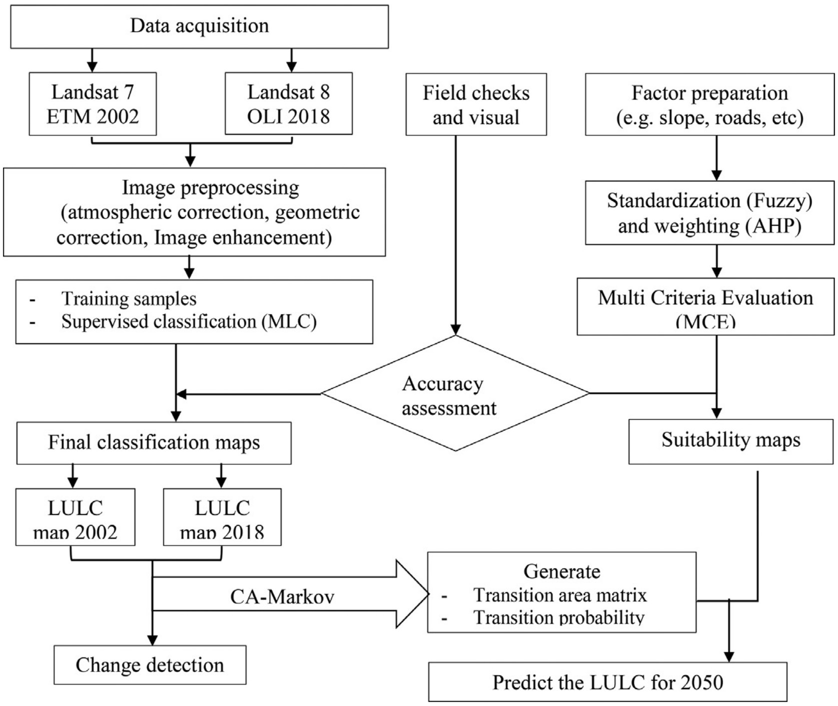

Fig. 2. Methodological framework for data processing.

were held to collect expert explanations and perceptions on the causes of land use and land cover changes including climate change.

The years 2002 and 2018 were selected to correspond to major socio-political and policy changes in Bhutan that has significant bearings on LULC in the city. Expansion of Thimphu city in 2002 added local areas of Lanjophaka, Heo-Samteling, Jungshi-Pamtsho, Taba and Dechenchol-ing in the north and Changjiji, Lungtenphu, Simtokha, and Babesa in the south (Fig. 1). Since then, what was previously lush paddy fields, fruit orchards, and fringe forests dotted with traditional Bhutanese houses were rapidly replaced by modern concrete buildings and other infrastructure such as roads, parking lots, etc., resulting in significant changes in Thimphu's landscape. The initiation of constitutional democracy in 2008, further accelerated the rate of infrastructure development including aggressive construction of commercial and residential areas, roads, service infrastructure. These hasty events triggered rapid conversion of land with little regard to social and environmental safeguards and as such a study to detect LULC changes would yield useful information for planners and policy makers.

Pre-processing and classification

Pre-processing is an important step to establish direct affiliation between the acquired data and biophysical phenomenon. Remotely sensed data are susceptible to radiance, geometric, and atmospheric distortions due to acquisition systems and platform movements. One major function of pre-processing is to remove such distortions especially when optical sensor data is used. Atmospheric correction involves removal of haze primarily originating from water vapor, fog, dust, smoke, or other particles in the atmosphere (Makarau, et al., 2014), which otherwise leads to distortion of reflectance. In addition, topographic normalizations are important for mountain environment such as Thimphu valley, as the presence of steep slopes can trigger variations in illuminations of identical features (Vanonckelen, et al., 2015). We imported the satellite data into TerrSet software and GIS and used its ATCOR (Atmospheric Topographic CORection) feature to remove haze and correct topographic normalization (Richter and Schlapfer, 2002) to generate images with true reflectance. To provide more accurate land use classification scheme both unsupervised and supervised (hybrid classification) approaches were used to derive five land use classes for Thimphu city (Table 2).

Table 2
Land cover classification scheme.

LULC Types	Description
Water body	Rivers, streams, ponds, lakes, reservoirs, and marshlands
Bare ground	Exposed soils, landfills, and areas of active excavation
Built-up area	Commercial areas, urban settlements, industrial areas, government and institutional buildings, roads, hard surfaces, parking areas, recreational areas, and golf courses,
Agriculture	Crop land (wetlands and drylands), and orchards
Forest	Plantations, broadleaf forests, conifer forests, and riparian vegetations

For unsupervised classification, hyper clustering (use of much higher number of clusters then the desired classes) was used as exact number of pixels were not known (Cihlar, 2000). These clusters were labelled as water body, bare ground, built-up area, forest, and agriculture on the google earth observation and other land use maps (MoWHS, 2008; Norbu, 2020 unpublished) of the study site. Spectrally similar classes of the identical land use type were merged. For each of the land use types, training samples were randomly generated from the satellite imagery. The signature points were then tested for statistical similarities (Rojas, et al., 2013) which indicated a good degree of similarity-based on spectral distance. This indicated minimum confusion between the land uses and as such considered satisfactory for the study (Gao, 2012). Visual interpretation was also used to resolve any issues related to mixed pixels and enhance classification accuracy.

The outputs were then subjected to supervised classification using the Maximum Likelihood Classifier (MLC). MLC classifier was used as it is a robust and popular algorithm increasingly used for classification of LULC (Lillesand, and Kiefer, 1999). MLC procedure uses a parametric statistical approach to prepare the probability density distribution functions for each individual land use class (Thom, 1994; Pielke, et al., 2002). Compared to other methods, MLC is considered to be more accurate as it calculates the total amount of variance and the correlation of the spectral values of different bands according to the specimen and uses this property for the association of pixels classified into one of the groups and is based on the most similarity between the pixels. In addition MLC also reflects the intensity of land use changes and the visual differences in land use types and considers not only the cluster center but also its shape, size, and orientation (Hailemariam, et al., 2016; Molla, et al., 2018). Resultant thematic raster layers were then used for post classification change detection. The use of high resolution google earth map and firsthand knowledge of the study area by the principal investigator considerably improved the results obtained using the supervised algorithm.

Assessment of classification accuracy

Assessment of classification accuracy is a prerequisite for classification data to credibly detect changes (Wang, et al., 2020). Accuracy assessment was carried out on the resulting classified imagery using error matrix and kappa index (Congralton, 1991; Keshtkar, et al., 2017) to test the precision and accuracy of imagery and comparing them with actual points from the field supplemented by 150 systematic points from high resolution google earth data. Kappa coefficient was calculated using the formula confirmed and used by Congralton and Green (2009);

$$\text{Kappa coefficient} = \frac{\sum_{i=1}^{k} nii - \sum_{i=1}^{k} nii\ (GiCi)}{n^2 - \sum_{i=1}^{k} nii\ (GiCi)} \tag{1}$$

Where, i is the class number, n is the total number of classified pixels that are being compared to actual data, n_{ii} is the number of pixels belonging to the actual data class i, that were classified with a class i, C_i is the total number of classified pixels belonging to class i and G_i is the total number of actual data pixels belonging to class i.

In order to deepen the understanding of major land uses and drivers of their changes and socio-environmental implications, the principal investigator carried out field visits in 2019. During the field visits, field observations and consultations were held with the stakeholders including communities, experts and local officials to collect biophysical and climatic data. Discussions were also held to acquire information about urban expansion, evolution of land use, possible reasons for the observed changes and resident perception on socio-environmental resilience. In addition, records of major incidents such as disasters (fire, floods), plantation efforts, policy changes, etc. were also noted. These information and firsthand experience from the field were used to further validate the classified images.

Land use and land cover change analysis

CA-Markov is a robust model that has outperformed other methods for simulating and predicting LULC types (Theobald and Hobbs, 1998; Kamusoka, et al., 2009; Guan, et al., 2011). Hence, this study selected the CA-Markov model for simulating and predicting LULC change. This process involved (1) carrying out Markovian chain analysis on the 2002 and 2018 LULC maps to generate transition area matrices; (2) generating transitional area maps of LULC; (3) evaluating the model accuracy to simulate future changes based on Kappa indices; and (4) predicting spatial distribution of LULC in 2050.

Markov chain analysis

The Markov model simulated changes in LULC from one time to another in order to predict future change. Markov chain analysis built in module at TerrSet was used to generate transition probability matrix (where the probabilities of transition represent the probability that a pixel of a given class will move to some other cell class in the next time period) and transition area matrix (which represents the total area (in cells) expected to change from one LULC class to another over the prescribed number of time units). The transition probability matrix is expressed in a text file that records the likelihood of moving each land use and land cover category to some other category, while the transition area matrix, also represented in a text file records the number of pixels required to transition from one land use and land cover class to another over the specified number of time unit (Fig. 2).

The Markovian chain analysis is represented as, $S(t,t+1) = Pij \times S(t)$, where, $S(t)$ is the system status at time of t, $S(t+1)$ is the system status at time $t+1$; Pij is the transition probability matrix in a state, which is calculated using the following formula (Li, et al., 2016; Khanal, et al., 2019):

$$\rho_{ij} = \begin{pmatrix} \rho_{11} & \rho_{12} & \cdots & \rho_{1n} \\ \rho_{21} & \rho_{22} & \cdots & \rho_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ \rho_{n1} & \rho_{n2} & \cdots & \rho_{nn} \end{pmatrix} \left(0 \le \rho_{ij} \le 1\right) \tag{2}$$

where, ρ is the Markov probability matrix, and ρ_{ij} stands for the probability of converting from current state i to another state j in next time period. Low transition will have a probability near (0) and high transition probability near (1). The 2002 LULC image of the Thimphu city was used as the base (t_1) image while 2018 LULC map as the later (t_2) image in this model to obtain the transition matrix between 2002 and 2018. In this study, ArcGIS cross-tabulation functionality was used to generate transitional area matrices by multiplying each column in the transition probability matrix by the number of pixels of corresponding class in the later image.

Transitional suitability maps

Multi-Criteria Evaluation (MCE) was used to build transition suitability maps which show the probability of a pixel to change to another class or remain unchanged. MCE integrates various driving factors to derive a single index of evaluation (El-Hallaq and Habboub, 2014). These driving factors differ according to the conditions of the region under study (Rimal, et al., 2018). As this is the first study of its kind for Thimphu city, authors firsthand knowledge in combination with complexity of the terrain, socio-economic development, urban regulations, political changes, physical proximity to current LULC were used to define transition rules. Accordingly, distance to main road, distance to water bodies, distance to forests, distance to built areas, slope, were used in calculating transition suitability maps. The maps of road, and other infrastructure, along with DEM were obtained from the city office. Fuzzy membership functions were used to standardize factor maps into 0-1, where 0 represents unsuitable locations and 1 represents ideal locations. The Analytic hierarchy process (AHP) was used to derive the weights of driving factors.

The CA–Markov model

The transition probability matrix and transition area matrix from 2002 to 2018 calculated in Markov chain analysis. The area of each land class to be converted to another LULC classes was estimated based on the transition probabilities. These areas were divided by the total number of iterations (16 years) for the cellular automation to generate the areas to be converted per iteration. We applied a contiguity filter of 5×5 pixels to define the effect of neighboring cells on the central cell. The future assignment to a specific LULC class for each pixel was based on how much the pixel is suitable for that LULC class and how close the pixel is to other pixels of the same class. The new policy and political developments after 2001 and 2008 were assumed as in simulating future scenarios. The period, 2002–2018 represents a rapid expansion of the city accompanied by expediated socio-economic development that led to significant changes in the city's landscape. Assuming that these probabilities (2002-2018) will hold and using the interpreted map of 2018 as the base map, we finally predicted LULC in 2050.

Results and discussion

Classification accuracy

Model validation is an important precondition for studies that attempt to predict LULC changes (Appiah, et al., 2015). The Kappa statistic is one of the most popularly accepted methods for quantifying a model's predictive power (Maingi and March, 2002; Hua, 2017) and can take any values from -1 to +1 (Congralton and Green, 2009). Studies by

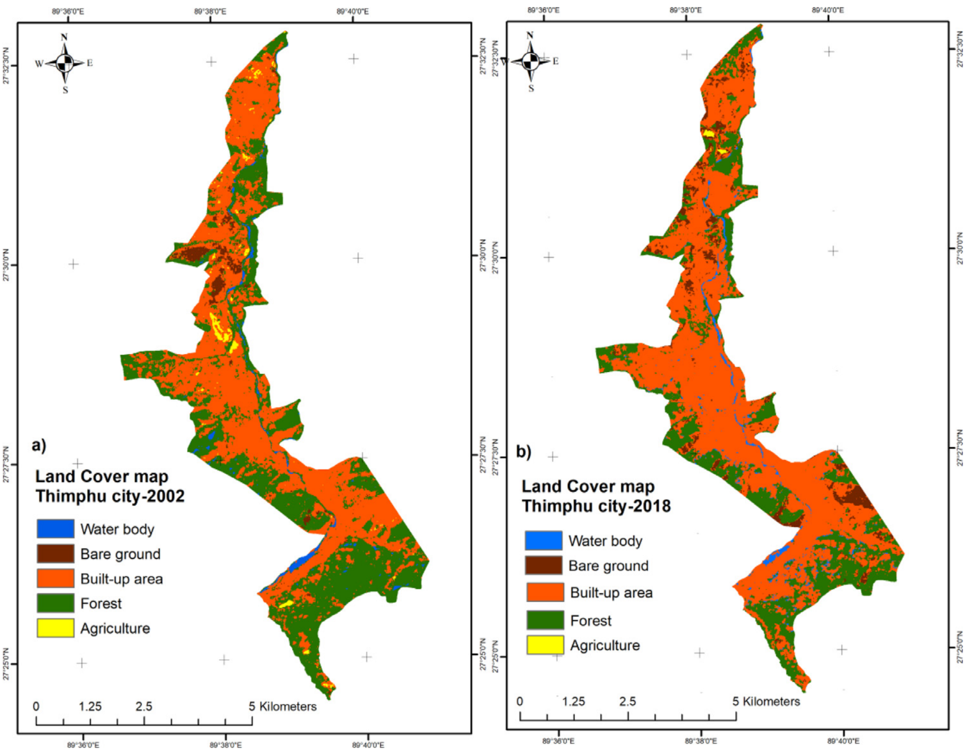

Fig. 3. Land use and land cover map of 2002 and 2018

Table 3
Composite table of area statistics (km^2) of Thimphu city 2002 and 2018.

LULC Types	2002		2018		Over all change 2002 - 2018	
	Area (km^2)	Area (%)	Area (km^2)	Area (%)	Area (km^2)	Area (%)
Water body	0.45	1.70	0.45	1.72	0.00	0.02
Bare ground	0.63	2.38	1.56	5.94	0.93	3.55
Built-up area	13.86	52.88	17.20	65.65	3.34	12.77
Forest	10.94	41.76	6.94	26.50	-4.00	15.25
Agriculture	0.32	1.20	0.05	0.19	-0.26	1.01
Total	26.20	100	26.20	100		

Manomani and Suganya (2010) and Maingi and Marsh (2002) have categorized kappa values into several groups: <0 indicate no agreement, 0-0.2 as slight, 0.0-0.41 as poor, 0.41-0.60 as moderate, 0.60-0.80 as significant, and 0.81-1.0 as almost perfect agreement. Kappa analysis for this study generated values well over 70, qualifying them as significant predictors (Manonmani and Suganya, 2010).

Analysis of land use and land cover types

LULC analysis allows us to understand biophysical changes such as: loss of productive ecosystems/biodiversity, deterioration of environmental quality, loss of forest and agricultural lands what are important information for planning sustainable cities (Mallupattu and Screenivasula, 2013).

Our study applied latest remote sensing and GIS techniques to quantify LULC in Thimphu city. Using the outputs from remote sensing imagery, field surveys, and topped expert knowledge of the study area, five LULC types were classified; water body, bare ground, built-up area, forest, and agriculture (Fig. 3). LULC analysis show that the extent of land cover types varied across the years and we explored the significant transformations between 2002 and 2018 (Table 3, Fig. 3). The area of land use types was calculated (Table 3) from the classified images of 2002 (a) and 2018 (b) presented in Fig. 3. Fig. 3 confirm that the built-up is most intense at the core of the city and radiates outwards. Forests are mostly confined to the marginal fringe lands located at higher grounds with some spotty patches scatted through the city and along the riparian zones. Bare ground is found scattered across the city while agriculture is confined to certain pockets only. In 2002, the largest land use types were built-up (52.88%), followed by forest (41.76%), and bare ground (2.38%). By 2018, city's built-up area increased the most from 13.86 km^2 to 17.20 km^2 (65.5%) reflecting an overall increase of 12.77% (3.34 km^2) in 2018 (Fig. 4). Concrete buildings for residential and commercial purposes, road networks, pavement, parking lots, recreational facilities, and other impervious surfaces were responsible for the expansion of built-up area in the city. This has significantly reduced the forest cover by 15.25% (4 km^2; Fig. 4) which is mostly confined to the periphery of the town especially in the south and north (Fig. 3). Currently, forest coverage of the city is only about 26% compared to 42% in 2002 (Table 3). Between 2002 and 2018, bare ground area has also increased by 3.55% (Table 3) due to increasing excavation, landfills, and exposure of soils. The results also show that the conversion of forest to other land use types remain high during the study period with built-up area consuming over 28% of the total forest loss (Fig. 4).

These expediated changes can be attributed to: i) governments approval for expansion of the city in 2002, followed by the hastened construction of city infrastructure post Bhutan's transition to democracy in 2008. The resultant improvement in basic facilities combined with creation of additional jobs further attracted more immigration from rural areas and lesser developed cities, causing a boom in real estate and informal settlements and triggering significant changes in land uses.

Studies by Bruggeman, et al. (2016) and Yangchen, et al. (2015) also confirmed infrastructure development especially by rapidly growing

Table 4
Land use class transition matrix from 2002 to 2018.

	LULC Types	2018 image (km^2)					
		Water body	Bare ground	Built-up area	Forest	Agriculture	Total
2002 image (km^2)	Water body	**0.17**	0.00	0.13	0.14	0.00	0.45
	Bare ground	0.00	**0.11**	0.49	0.02	0.00	0.62
	Built-up area	0.10	1.17	**11.83**	0.71	0.00	13.82
	Forest	0.15	0.55	4.25	**6.04**	0.00	10.94
	Agriculture	0.00	0.01	0.21	0.08	**0.01**	0.31
	Total	0.66	1.56	16.92	6.99	0.01	26.14

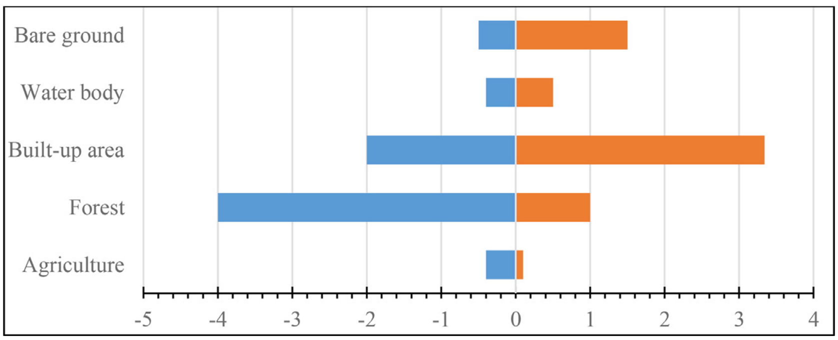

Fig. 4. Gains and losses between 2002 and 2018.

cities such as Thimphu as a primary cause of forest loss in Bhutan. Globally, the loss of forest and other land types in Thimphu city is a typical trend observed in urbanization especially in developing countries (Sun, et al., 2013; Pandey and Seto, 2015; Kegazy and Kaloop, 2015; Bruggeman, et al., 2016). It is generally proven that the loss of forest and vegetative cover will degrade ecosystem services by reducing water retention, drying of water sources, loss of habitat for biodiversity, reduced sequestration rate of CO_2, and enhancing the magnitude and frequency of disasters such as flash floods, landslides, and scarcity of water and other natural resources, which are vital for human wellbeing (Woldeamlak, 2002). Loss of forest and vegetative cover can amplify island heat affect in cities such as Thimphu which is located in a deep valley surrounded by high mountains on all sides. Gogoi, et al. (2019) simulated the impact of LULC on surface temperature over eastern India and found that 20–50% of the observed warming were associated with LULC. They further confirmed that largest changes were linked to changing vegetation cover. Given that the current trend of LULC is mainly triggered by building infrastructure in the face of limited size of various land use types, it won't be long before the city's growth will use the available bare ground and expand development into existing forest, riparian areas, and may even continue encroaching into the government reserve forests on the surrounding hills. Such a scenario is highly undesirable as it will further degrade the fragile watersheds and destabilize ecological functions including providing water which is already in short supply. The city is currently grappling with problems of water shortage, expansion of squatter settlements, sanitation, flooding of storm drains during rainy seasons, etc. Some sections of the city including those in informal settlements have irregular or no supply of drinking water. Under the business as usual scenario and expected impacts from global climate change, there is an urgent need to step up adaptation and mitigation interventions including massive plantation in vacant spaces and roads, as well replace hard surfaces with vegetation.

LULC transition between years

To deepen our understanding of the evolving nature of the LULC types in the city, we created confusion matrices for changes in 2002 and 2018 (Table 4). All unchanged pixels are presented diagonally in bold fonts. The details of land cover transition between the 5 land use types are mapped in Fig. 5. Corresponding transitional probability is also tabulated into Table 5. During the study period, built-up area is the most stable land use type with a transition probability of 0.82. This implies that it the probability of built up area transitioning into other land use types is very low. Although low, it's encouraging to see forest type retaining some stability, this is probably due to some plantation efforts that the Government have initiated recently. The most dynamic land use types are bare ground, agriculture, and forest with transition probabilities of 0.10, 0.01, and 0.34 respectively. Most land types were also converted to built-up areas with the largest area coming from forest (4.25km^2) followed by bare ground (0.49km^2).

The potential for these trends to continue remain high with transition probabilities of 0.83 for bare ground and 0.58 for forest to transition to built-up area. Although small, agriculture land shows a significant probability to transition to built-up area which has been the trend in many cities (Pandey and Seto, 2015; Rimal, et al., 2018; Ishtiaque, et al., 2017), and represent future threat to existing agricultural land adjoining the city. A slight but interesting transition of forest to water body could have been the result of clearing forests along the river and streams exposing larger water surfaces. Fig. 5 confirms these transitions and show the transitions spatially. It is clear from Fig. 5 that most of the conversions are occurring in the newly extended areas in the north and south as well as along the fringes of the core area. This is because the central core is already built to almost its full capacity forcing infrastructure construction to extend south and north after 2002. Most intense conversion from forest to built-up took place in Babesa and Serbithang areas in the southern extension of the city. A lot of the bare ground in the northern extension of the city transitioned to built-up area. Bare grounds in this part of the city were previously agricultural land left fallow in anticipation for development after inclusion in the city in 2002.

The findings indicate that rapid development of urban built will lead to sharp declines in forest and agriculture and increase in urban population. These developments could jeopardize ecosystem health, human well-being, and food security (Rahman, 2016; Khanal, et al., 2019). Further, most of forest conversions are taking place in higher grounds and watersheds, which could expose bare ground and make them vulnerable to gully erosion (Miheretu and Yimer, 2017) which can cause serious damages especially in fragile and rugged terrain like Thimphu. In addition, increased population could result in increased pollution and excessive extraction of natural resources which could lead to detrimental consequences including urban heat wave (Gogoi, et al., 2019), landslides, and health problems (Hansen, et al., 2013).

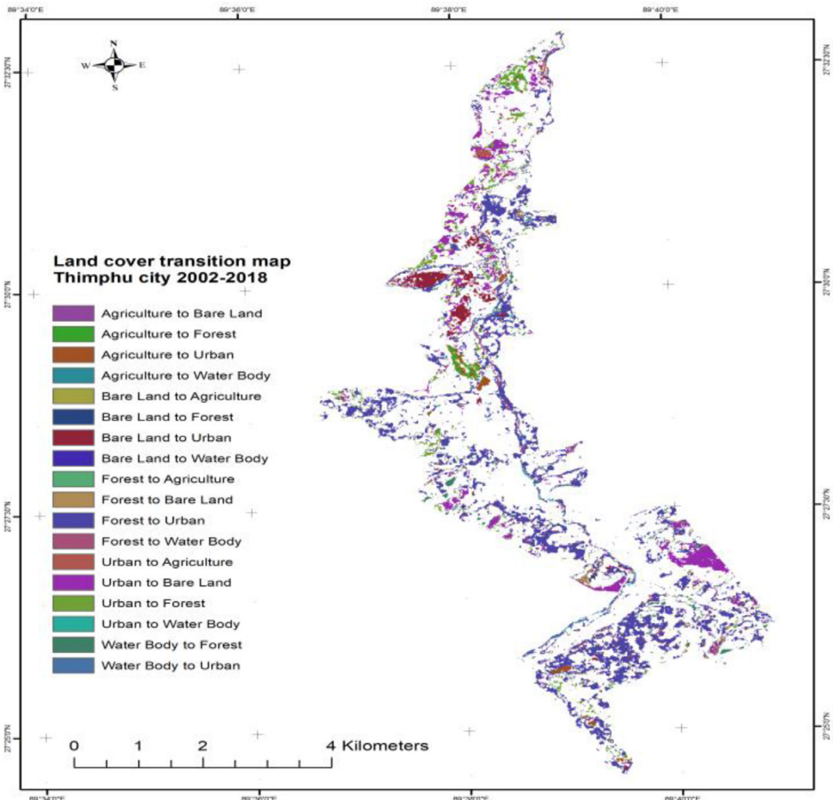

Fig. 5. LULC transition map of Thimphu city.

Table 5
Land use transition probability matrix from 2002–2018.

		2018 image (km^2)				
		Water body	Bare ground	Built-up area	Forest	Agriculture
2002 image (km^2)	Water body	0.17	0.03	0.49	0.31	0.00
	Bare ground	0.01	0.10	0.83	0.06	0.00
	Built-up area	0.01	0.09	0.82	0.08	0.00
	Forest	0.02	0.08	0.58	0.32	0.00
	Agriculture	0.01	0.07	0.72	0.19	0.01

Table 6
Predicted land use and land cover for 2050.

LULC types	Area (km^2)	Area (%)
Water body	0.46	1.74
Bare ground	2.20	8.40
Built-up area	19.24	73.43
Forest	4.28	16.32
Agriculture	0.03	0.12

Prediction of land use land cover change

Results of LULC prediction using CA-Markov analysis are shown in Table 6 and Fig. 6. Predicted figures for 2050 show further decrease in the forest (16.32%) and agriculture (0.12%) land use types which compared to 2018 figures (Table 3) represent a loss of 10.18%, and 0.07%, respectively. These losses are gained by built-up area (7.78%) and bare ground (2.46%) taking their total coverage to 19.24km^2 (73.43%) and 2.20km^2 (8.40%) respectively.

Fig. 6 show the predicted spatial destruction of LULC in 2050. Overall, forest cover is fragmented with larger patches remaining mainly in the south of the city along the river and on the fringes on higher grounds. Small and narrow patches of forests are also seen scattered across the city especially along streams, rivers, and marshlands. Fig. 6 also reconfirm the findings that most of what is covered by forest in 2018 will transition into built-up and bare ground. The presence of bare ground indicates soil excavations probably from the last wave of construction and landfills. These findings are reflective of the current urbanization trend and government policy. The predicted trends of urban built slowly or rapidly taking over other important land types such as forest and agriculture are similar to those reported by other urbanization studies (Huang, et al., 2008; Han ad Song, 2015; Appiah, et al., 2015; Rimal, et al., 2018; [13,22,26,51] in developing countries. If Thimphu city is to avoid irreversible problems that are plaquing many global cities, the city must shift form present business model to urgently adopt ecosystem based approach to urban development.

Conclusion

This study represents a first ever attempt to simulate the process of land use dynamics and the effects of physical, demographic, and socio-economic driving forces on LULC in Bhutan's capital city of Thimphu using remote sensing and GIS technology. Results clearly confirm significant changes in LULC from the start of expansion to current area in 2002 to 2018. Significant increase in built-up areas were associated with parallel loss of important land cover types such as forest and agriculture. Significant changes in Thimphu's landscapes are correlated with

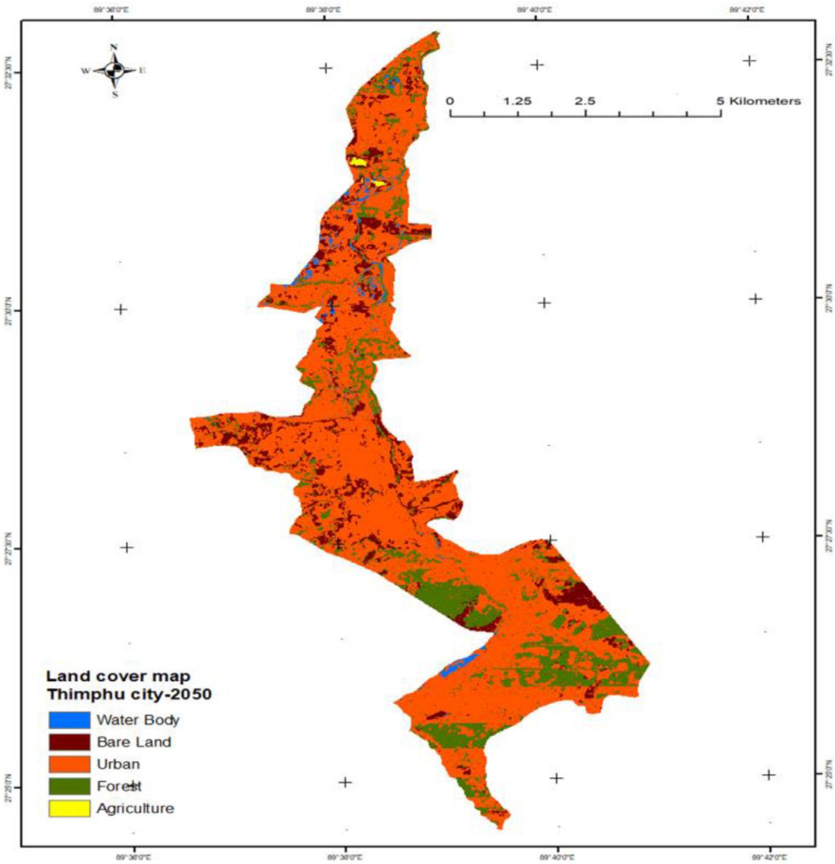

Fig. 6. Predicted LULC map of Thimphu city in 2050.

the government's decision to expand the city northwards and southwards. This expansion received a boost after the institution of constitutional democracy in 2008 which brought in expediated development in the city. These two policy events topped with rapid population growth mainly from rural urban migration for better opportunities and development activities expediated the LULC changes in the city. Combined these factors have reduced and fragmented forest cover which will degrade ecosystem services that are vital for maintaining the quality of human wellbeing in the city. Reports from the city residents also confirm that the impacts of these changes especially in the face of climate change are disproportionately felt by the most vulnerable groups such as low income, women, and children. The results of prediction for 2050 also did not bear well for Thimphu city, with forest cover diminishing to a mere 4.28km^2 (16.32%) which are also highly fragmented. Loss of forest cover will degrade important ecological services and increase vulnerability of the city to landslides, gulley erosion, drying of water sources, worsened air pollution, and loss of important biodiversity. More studies are recommended to especially monitor the impact of these changes and identify adaptive and mitigative interventions for a more sustainable city.

Study also show that remote sensing and GIS are effective tools for simulating urban changes, which are useful for guiding urban planning and management. The findings of this study are useful to policy makers, urban planners, and citizens to adopt better environmental management practices including adaptation and mitigation strategies for the city and its surrounding areas. The study recommend an ecosystem based adaptation policies and other legal frameworks should be developed and practically implemented to protect the current forest cover as well as rehabilitate and improve the existing green spaces in and around the urban centers. Such efforts must focus on planting fruit trees in urban spaces such as parking lots, between buildings, back yards, and along roads. These will significantly, increase water retention, protect soil from erosion, host biodiversity, as well as regulate temperature and pollution. Current capacities of storm drains and water reservoirs must also be enhanced. Informal settlements must either be formalized by providing all basic facilities or moved to formal settlements. We also caution the city to restrain from land filling flood plains and use the claimed land for building infrastructure as these areas are not only prone to flooding especially global lake outburst floods but also important for biodiversity. We encourage the city planners and experts to use the findings and recommendations from our study to avert irreversible changes to its LULC.

The accuracy of the classification results was not perfect due to the hilly nature of the study area, where ground changes in altitude can impact the image pixel value. However, it is significant and as such study findings and recommendations can be applied to other cities in Bhutan and other mountainous countries which share similar ecological and socioeconomic characteristics.

Declaration of Competing Interests

Authors have no competing interests.

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