Environ Monit Assess (2019) 191: 255
https://doi.org/10.1007/s10661-019-7389-0

Simulating urban expansion in a rapidly changing landscape in eastern Tarai, Nepal

Bhagawat Rimal · Hamidreza Keshtkar · Roshan Sharma · Nigel Stork · Sushila Rijal · Ripu Kunwar

Received: 14 December 2018 / Accepted: 13 March 2019 / Published online: 28 March 2019

Abstract Understanding the spatiotemporal dynamics of urbanization and predicting future growth is now essential for sustainable urban planning and policy making. This study explores future urban expansion in the rapidly growing region of eastern lowland Nepal. We used the hybrid cellular automata-Markov (CA-Markov) model, which utilizes historical land use and land cover (LULC) maps and several biophysical change driver variables to predict urban expansion for the years 2026 and 2036. Transitional area matrices were generated based on historical LULC data from 1996 to 2006, from 2006 to 2016, and from 1996 to 2016. The approach was validated by cross comparing the actual and simulated maps for 2016. Evaluation gave satisfactory values of Kno (0.89), Kstandard (0.84), and Klocation (0.89) which verifies the accuracy of the model. Hence, the CA-Markov model was utilized to simulate the LULC map for the years 2026 and 2036. The study area experienced rapid peri/urban expansion and sharp decline in area of cultivated land during 1989–2016. Built-up area increased by 110.90 km^2 over a period of 27 years at the loss of 87.59 km^2 cultivated land. Simulation analysis indicates that urban expansion will continue with urban cover increasing to 230 km^2 (8.95%) and 318.51 km^2 (12.45%) by 2026 and 2036, respectively, with corresponding declines in cultivated land to 1453.83 km^2 (56.86%) and 1374.93 km^2 (53.77%) for the same years. The alarming increase in urban areas coupled with loss of cultivated land will have negative implications for food security and environmental equilibrium in the region.

Keywords Urban expansion · Spatial models · CA-Markov · Developing countries · Food security

B. Rimal (✉)
College of Applied Sciences (CAS)-Nepal, Tribhuvan University, Kathmandu 44613, Nepal
e-mail: bhagawatrimal@gmail.com

H. Keshtkar
Department of Remote Sensing and GIS, Faculty of Geography, University of Tehran, Tehran, Iran
e-mail: Hkeshtkar@ut.ac.ir

H. Keshtkar
Faculty of Natural Resources, University of Tehran, Karaj, Iran

R. Sharma
Center for Urban Research, RMIT University, 124 La Trobe St, Melbourne, VIC 3004, Australia
e-mail: roseanstore@hotmail.com

N. Stork
Environmental Future Research Institute, Griffith School of Environment, Nathan Campus, Griffith University, 170, Kessels Road, Nathan, QLD 4111, Australia
e-mail: nigel.stork@griffith.edu.au

S. Rijal
Central Department of Sociology, Tribhuvan University, Kathmandu 44613, Nepal
e-mail: sushilarijal@ymail.com

R. Kunwar
Cultural and Spatial Ecology, Department of Geosciences, Florida Atlantic University, Boca Raton, FL 33431, USA
e-mail: ripukunwar@gmail.com

Introduction

Urbanization is a global, complex, and dynamic process (Fisk 2012; Nagendra et al. 2018) and is an indicator of modernization, socialization, economic progress, and power (Mountjoy 1978). The process of urbanization is the outcome of a range of factors which vary according to time and space (Asma et al. 2017). In the present scenario, unprecedented urbanization has taken place due to various socio-economic forces (Umar and Indo 2018) mostly in third world cities (Kaplan et al. 2004). The world population totalled 7 billion in 2011 and is expected to reach 8.6 billion by 2030, 9.8 billion by 2050, and 11.2 billion by 2100 (UNDESA 2017). According to the World Urbanization Prospects 2018 Revision Report (UNDESA 2018), urban area accommodates 55% of the world's population in 2018. The current level of urbanization in Asia and Africa is relatively low, 50% and 43%, respectively, but with the global urban population projected to reach 6.7 billion (68%) by 2050, 90% of the urban population increase will be in Asia and Africa. The annual urbanization rate for the Asia and Pacific region was 2.3% compared with the average rate of global urbanization of 2%, and countries with least-developed economies have the highest rates of urbanization (UNESCAP 2015). For instance, the annual urban growth rate of Nepal (6.6%) is the high compared with that of other neighbor South Asian countries such as Sri Lanka (2.2%), Pakistan (4.4%), India (2.9%), and Bangladesh (5.3%) (Thapa and Murayama 2010). Other South East Asian countries with transitional economies have experienced similar urban population increases between 1980 and 2012: Cambodia 9% to 20%; Laos 12% to 32%; Myanmar 24% to 33%, and Vietnam 19% to 35% (Ouyang et al. 2016).

Nepal is one of the most rapidly developing South Asian countries with urban population as a percentage of the total population increasing from 2.9% in 1952/54 to 3.6% in 1961, 4.0% in 1971, 6.4% in 1981, 9.2% in 1991, 13.9% in 2001, and 17.1% in 2011 and the number of urban centers increasing from 10 to 58 (CBS 2014). By 2017, urban centers totalled 292 and contained more than 50% of the total population (MoFALD 2017).

Most urbanization in the developing world takes place without appropriate planning, and as a result is subject to many challenges. The socioeconomic gap between rural areas and highly urbanizing areas is widening. Urban slum areas are deprived of adequate access to basic services, including transportation, clean water, sanitation, hospitals, suffering from traffic congestion, urban poverty, urban unemployment, high urban costs, poor housing, and environmental degradation (Zhang 2016). Meanwhile, rapid urbanization (Julius Oluranti 2018) has led to conversion of prime farmland, potentially threatening sustainability (Seto et al. 2012; Yan et al. 2015), biodiversity, and economic function (Wu et al. 2011). Pollution, energy inefficiency, inflated infrastructure, and local and regional climate change are additional challenges caused by urbanization (Asma et al. 2017). Thus, understanding the spatiotemporal dynamics of urbanization and LULC may contribute to more effective planning, and may provide a sound foundation for the formulation of sectoral plans, insure more of sustainable urban futures, and maintenance of environmental equilibrium. Geographical information system (GIS) and remote sensing (RS) are used around the world (Al-Quraishi 2013; Keshtkar et al. 2017; Rimal et al. 2018d) for the assessment and simulation of spatial and temporal analyses of Earth's environment and land resource dynamics (Cholhyok et al. 2018; Khudair et al. 2018; Rimal et al. 2018c; Sexton et al. 2013; Yadav et al. 2018). These are important tools as they help us to understand the drivers and dynamics of LULC transformation (Meiyappan et al. 2017; Rai et al. 2018) and may predict future environmental change (Campbell 1996; Markus 2017; Thapa and Murayama 2012). Monitoring the causes of and trends in land-use change and urbanization is essential to understand and simulate the change dynamics at different temporal and spatial scales (Keshtkar and Voigt 2015) and is a fundamental prerequisite for the formulation of effective urban policies, economic, demographic, and environmental plans to ensure sustainable development (Feng et al. 2017; Li et al. 2013; Wu et al. 2011).

Modeling and simulating spatial dynamics of urban expansion and LULC change under different scenarios are essential for urban planners and policy makers to understand what urbanization may be like in the future. They are the urban development models which simulate the events and their spatiotemporal consequences (Asma et al. 2017; Batty 2005). LULC change and urban growth simulation models (UGSM) are used to capture fundamental and compound relationships in time and space. Many different models have been used including the CA-Markov model (Corner et al. 2014; Jokar Arsanjani et al. 2013; Keshtkar and Voigt 2015;

Rimal et al. 2018a; Shafizadeh Moghadam and Helbich 2013; Traore et al. 2018; Wang et al. 2018a, b), logistic regression (LR) (Jokar Arsanjani et al. 2013; Verburg et al. 2004), SLEUTH (Clarke 2018), DINAMICA (Rodrigues and Soares-Filho 2018), CLUE (Verburg et al. 2015; Verburg 2004), SERGoM (Theobald 2005), and LUCAS (Sleeter et al. 2017). Markov chain, the statistical model, simulates the future state of LULC on the basis of past evidence by calculating the transition probability matrix (Jokar Arsanjani et al. 2013) while cellular automata, the spatiotemporal model, is capable of exploring the interrelationship among spatial cells (Han et al. 2009). The CA-Markov model, by integrating the advantages of CA-Markov effectively simulates the spatiotemporal status of LULC (Keshtkar et al. 2017).

In this study, we aim to simulate the future change of rapidly urbanizing eastern region of Nepal by 2026 and 2036 using the CA-Markov model. Previous studies have evaluated the urbanization process of different cities of Nepal including the entire Tarai region (Rimal et al. 2018d). Continuous replacement of cultivated land with new urban areas and rapid population growth have become increasing concerns. However, no one has attempted to explore future trends of urban expansion of the rapidly urbanizing area of eastern Tarai and that is the aim of the current study.

Method

Study area

In the study, we used the rapidly urbanizing area of southeast part of Nepal which is geographically enclosed between 26°21′43″ and 26°48′5” North latitude and 87°38′8″ to 88°12′00″ East longitude and covers 2556 km^2. It includes the rapidly urbanizing Morang and Sunsari districts of eastern Nepal including three large cities: Biratnagar metropolitan, Itahari sub-metropolian, and Dharan sub-metropolitan (Fig. 1). The area is experiencing rapid population growth; the total population of the region was 1.1 million in 1991, increasing to 1.5 million, in 2001 and 1.7 million in 2011 (CBS 2014).

Data

For the evaluation of LULC analysis and simulation of the future change of the LULC, we used the LULC data developed by Rimal et al. (2018d) (Table 1). These data were prepared using freely available surface reflectance Landsat images for the years 1989, 1996, 2001, 2006, 2011, and 2016 (TM, ETM+ and OLI; Path/row 139/41 and 42 and 140/41 and 42) with high accuracy (Rimal et al. 2018d). A 30-m digital elevation model (DEM) was prepared from the data collected from the shuttle radar topographical mission (SRTM) (https://lta.cr.usgs.gov). LULC transition rates for the different time periods were explored using existing LULC data for the study area. Additional sub-regional based data were collected from the District Development Committee (DDC) (e.g. www.ddcmorang.gov.np and www.ddcsunsarigov.np). Administrative boundary data were collected from the Department Survey of Government of Nepal (GoN 2017).

The LULC classes identified include urban (built-up), cultivated land, vegetation, sand, and water areas. Population data were acquired from the Central Bureau of Statistics (CBS) (CBS 2014).

Simulating urban expansion

The CA-Markov model was used to predict future LULC change. This hybrid model predicts the future transformation of LULC on the basis of past data (Keshtkar and Voigt 2015; Rimal et al. 2018a). This model runs land change predictions for a preordained future time period through the historical transition matrix, imported from MC analysis, and the production of transition potential maps by multi-criteria evaluation (MCE) (Wang et al. 2018b).

The process of modeling includes the following steps (Keshtkar and Voigt 2016): (a) generating LULC maps of equal time intervals (here, 1996, 2006, and 2016); (b) exploring the magnitude of transition area CA-Markov model; (c) preparing transition probability maps using the MCE technique, analytic hierarchy process (AHP) model, and fuzzy membership functions; (d) validating the model by comparing actual maps (i.e., classified images) and simulated maps; and (e) simulation of future LULC maps (here, 2026, and 2036).

Transition potential maps

Based on historical LULC changes in the area (Rimal et al. 2018d) (Table 2), several biophysical change drivers were identified. These included distance to built-up areas, forest, roads, water bodies, and slope

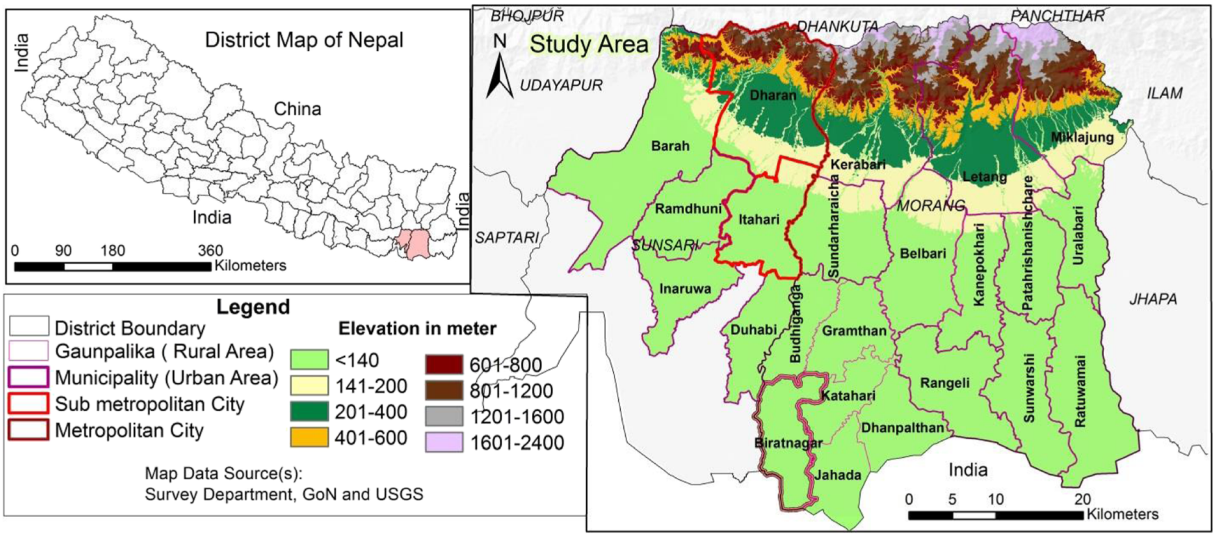


Fig. 1 Location map of the study area

and data for each of these drivers were obtained from a range of sources. Slope layer was derived from a digital elevation model (DEM) with a horizontal grid size of 1 arc sec (30 m), obtained from shuttle radar topography mission (SRTM) dataset. Distance to the road, water bodies, built-up area, and vegetation and cultivated lands were created based on the Euclidean distance from existing land use maps. To regulate the weight of driving factors, an analytic hierarchy process (AHP) model was used. Before importing the driver maps to the AHP model, they were rescaled to the range 0–1 using fuzzy membership function (Table 3). Based on the CA-Markov model, a transition potential matrix was computed. This matrix records the number of cells of each category that are expected to change to another category in a given period in the future (Keshtkar and Voigt 2016). Here, transitional area matrices were generated based on the historical LULC data from 1996 to 2006, from 2006 to 2016, and from 1996 to 2016 (Table 2). Finally, the LULC map for the year 2026 and 3026 were simulated using the CA-Markov model.

Model evaluation

Several Kappa variations were used to measure the simulation success of the model. For this, the LULC map of 2016 was compared with the simulated map of the same year. Above 80% of achieved standard accuracy approved the model's potent prediction (Araya and Cabral 2010; Keshtkar and Voigt 2016). Validation of the model was performed using Kno, Kstandard, and Klocation. Kno index is more reliable than Kstandard index for assessing the overall accuracy (Keshtkar and Voigt 2015). In addition, we assessed the accuracy of the model through quantity disagreement and allocation disagreement parameters as suggested by Pontius et al. (Pontius and Millones 2011). Details of the Kappa indices

Table 1 Data types and sources

Data	Source	Date	Format
LULC data	Rimal et al. 2018d	1989, 1996, 2001, 2006, 2011, and 2016	Raster
Administrative boundary	Survey Department, Government of Nepal	2017	Vector
Population data	Central Bureau of Statistics (CBS), Nepal	1981, 1991, 2001, and 2011	Text
District Profile and District Transport Master Plan	District Development Committee (DDC) (e.g.www.ddcmorang.gov.np and www.ddcsunsari.gov.np)	Morang-2014, Sunsari-2014	Text

Table 2 LULC statistics during 1989–2016 (area in km^2 and percentage)

LULC	1989		1996		2001		2006		2011		2016	
	km^2	%	km^2	%	km^2	%	km^2	%	km^2	%	km^2	%
Urban	29.20	1.14	41.29	1.61	60.41	2.36	76.23	2.98	111.33	4.35	140.10	5.48
Cultivated	1628.62	63.70	1617.38	63.26	1598.21	62.51	1590.64	62.21	1556.91	60.89	1529.79	59.83
Vegetation	727.96	28.47	713.41	27.90	710.48	27.79	702.63	27.48	712.51	27.87	714.39	27.94
Sand	100.06	3.91	104.09	4.07	106.49	4.16	116.81	4.57	111.56	4.36	87.66	3.43
Water	70.98	2.78	80.65	3.15	81.23	3.18	70.51	2.76	64.50	2.52	84.88	3.32
Total	2556.82	100	2556.82	100	2556.82	100	2556.82	100	2556.81	100	2556.82	100

and disagreement parameters are given elsewhere (Keshtkar and Voigt 2015; Pontius and Millones 2011). After successful validation, simulation was performed to predict the LULC of the study area for the years 2026 and 2036.

Urban expansion and orientation analysis

Exploring the spatial direction and extent of urban expansion is essential for the future urban planning. For the analysis, linings were generated in every 2-km distance using Arc GIS 10.1 and the study area was divided into eight equal subsections through the straight waves drawn at 45° angles from the assumed center. The subsections are named as North, North-East, East, South-East, South, South-West, North-West, and North (hereafter, N-NE, NE-E, E-SE, SE-S, S-SW, SW-W, W-NW, WN-N).

Urban growth rate

Urban growth rate refers to the average annual rate of expansion in the corresponding years (Yin et al. 2011). For this, the following formula was used:

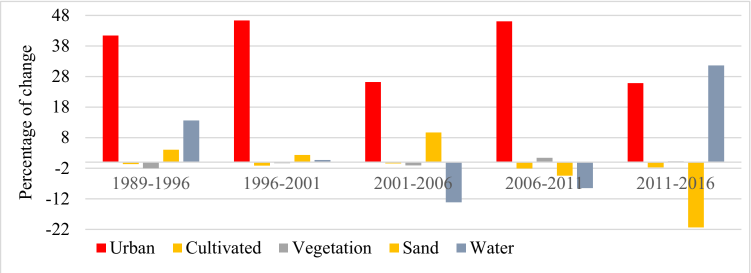
$$\mathrm{AUER} = (S_2 - S_1)/(T_2 - T_1) \times 100 \quad (1)$$

where AUER refers to average urban expansion rate (km^2/year), S_1, S_2 are the settlement areas in km^2 during the time (years) T_1 and T_2.

Table 3 Control points and individual weights of driving factors

Factors	Suitability	Control points	Functions	Weights
Distance-roads	High	0–500 m	J-shaped	0.25
	Medium	500–5000 m		
	Low	> 5000 m		
Distance-forests	No	0–500 m	Linear	0.12
	Medium	500–5000 m		
	High	> 5000 m		
Distance-water bodies	No	0–100 m	Linear	0.12
	Medium	100–7500 m		
	High	> 7500 m		
Distance-built-up areas	High	0–100 m	Linear	0.35
	Medium	100–5000 m		
	Low	> 5000 m		
Slope	High	0%	Sigmoid	0.16
	Medium	0–15%		
	No	> 15%		

Fig. 2 Change of LULC from 1989 to 2016



Result

Historical LULC change analysis 1989–2016

According to the historical LULC change analysis, considerable changes in several LULC classes occurred during 1989–2016. The overall changes include the gradual increase of urban/built-up area, decline of cultivated land, and fluctuations in areas of vegetation, sand, and water bodies (Table 2, Figs. 2 and 3). Built-up area experienced a large increase of 110.90 km^2, from 1.14 to 5.48% with an average annual growth rate of 14.06%. There was a corresponding decrease in cultivated land area by 98.83 km^2, from 63.70 to 59.83%, over the same period.

During 1989–1996, urban/built-up area exhibited a gradual increase from 29.20 km^2 (1.14%) area to 41.29 km^2 (1.64%) with the average annual growth rate of 5.91%. The cultivated land area that covered 1628.62 km^2 (63.70%) in 1989 declined by 11.24 km^2 and totalled 1617.38 km^2 (63.26%)

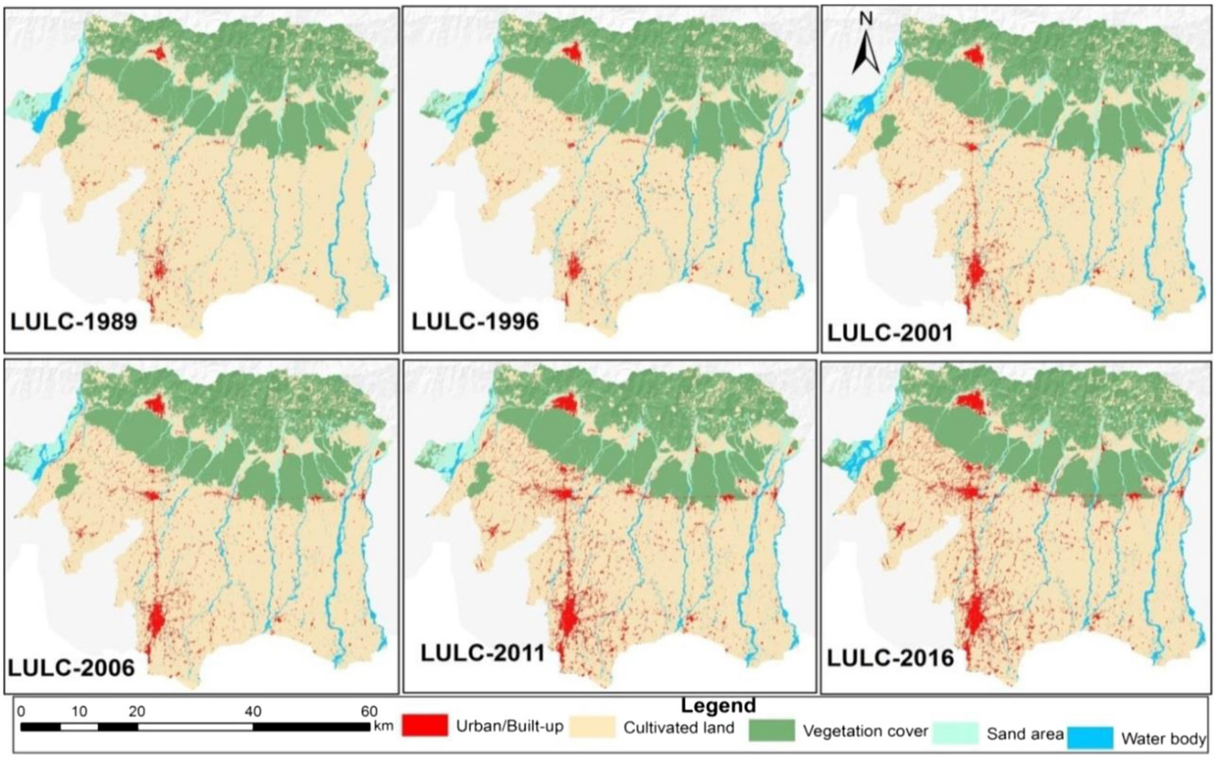


Fig. 3 LULC change trend maps during 1989–2016

Table 4 Transition probability matrix of LULC types for the periods 1996–2006, 2006–2016, and 1996–2016

	LULC type	Built-up	Cultivated	Forest	Sand	Water
1996–2006	Built-up	0.8430	0.1401	0.0056	0.0104	0.0008
	Cultivated	0.0765	0.8659	0.0300	0.0189	0.0087
	Forest	0.0051	0.0981	0.8619	0.0345	0.0004
	Sand	0.0098	0.0652	0.0753	0.7387	0.1111
	Water	0.0136	0.0932	0.0046	0.2357	0.6529
2006–2016	Built-up	0.8352	0.1496	0.0077	0.0033	0.0042
	Cultivated	0.1093	0.8515	0.0283	0.0049	0.0060
	Forest	0.0140	0.0777	0.8795	0.0263	0.0025
	Sand	0.0329	0.0774	0.1142	0.5982	0.1773
	Water	0.0299	0.0596	0.0016	0.0970	0.8119
1996–2016	Built-up	0.8456	0.1407	0.0047	0.0060	0.0029
	Cultivated	0.1279	0.8323	0.0262	0.0058	0.0078
	Forest	0.0167	0.0946	0.8633	0.0242	0.0012
	Sand	0.0283	0.0701	0.1270	0.6100	0.1645
	Water	0.0422	0.1016	0.0023	0.1326	0.7213

area in 1996. In the following period (1996–2001), average annual urban growth rate exponentially increased to 9.26% by adding 19.12 km^2 totalling 60.41 km^2 (2.36%) of urban/built-up area whereas cultivated land declined by 19.17 km^2 or reached to 1598.21 km^2 (62.51%) in 2001.

In the subsequent period, 2001–2006, the urban expansion trend continued, however, the annual growth rate reduced to 5.23%. Urban/built-up area increased by 15.82 km^2, totalling 76.23 km^2 (2.98%). Cultivated land area declined by 7.57 km^2 totalling 1590.64 km^2 (62.21%) in 2006. The largest urban expansion and the cultivated land loss occurred during 2006–2011. Urban area increased by 35.1 km^2 (4.35%) while to its contrary, cultivated land area declined by 33.73 km^2 (60.89%) (Table 2). In 2011–2016, urban area increased by an additional 28.77 km^2 with an average annual growth rate of 5.16% covering in total 140.10 km^2 (5.48%) again at the expense of cultivated land and vegetation cover. Meanwhile, cultivated land area decreased by 27.12 km^2 and totalled 1529.79 km^2 (59.83%) by 2016 (Fig. 3).

LULC modeling and validation

To validate the results, the actual map of 2016 was compared with the simulated map of the same year and various kappa statistics were computed. The evaluation showed that the value of Kno was 0.89, Kstandard was 0.84, and Klocation was 0.89.Also, the analysis of modeling in terms of allocation and quantity parameters shows the allocation disagreement (6%) which is slightly higher than quantity disagreement (2.8%). Thus, according to the results acquired from Kappa indices and disagreement parameters, the CA-Markov model was able to predict urban expansion for the study region with high accuracy. The transition probability matrix 1996–2006, 2006–2016 (Table 4) and forecasted LULC maps for 2026 and 2036 are displayed in Fig. 4 (c) and 4 (d).

Simulation analysis shows that urban expansion will continue to increase to cover 229.05 km^2 (8.95%) and 318.51 km^2 (12.45%) by 2026 and 2036, respectively, with the corresponding declines in cultivated land to 1453.83 km^2 (56.86%) and 1374.93 km^2 (53.77%) for the same years (Table 5, Fig. 4). In addition, the

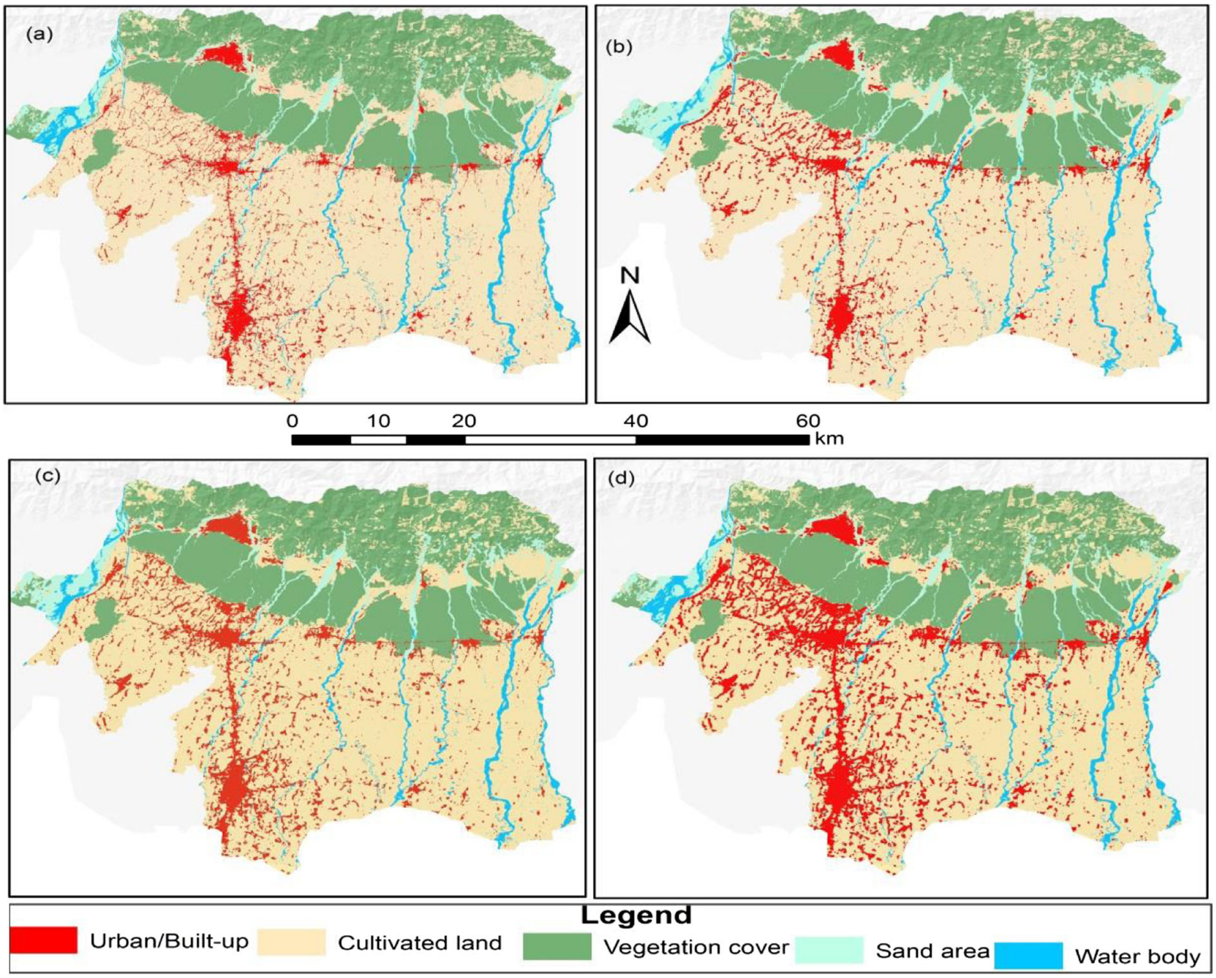


Fig. 4 LULC maps. **a** classified map of 2016. **b** predicted Map of 2016. **c** predicted map for 2026. and **d** predicted map for 2036

resulting land use change will result in a reduction in forest area from 714.39 km^2 in 2016 to 689.81 km^2 in 2026 and to 680.59 km^2 in 2036. Average annual urban growth rate, which was 6.36% during 1996–2016, could increase to 11.96% during 2016–2036. Results also show that urban area will expand in the periphery of the existing city centers, adjacent to major highways running east-west and north-south.

Table 5 Statistical information of LULC classes (in km^2) and annual change rates for 2016–2036

	Year			Change in LULC Structure		
	2016	2026	2036	Δ% 2016–2026	Δ% 2026–2036	Δ% 2016–2036
Built-up	140.10	229.05	318.51	38.51	28.08	55.77
Cultivated	1529.15	1453.83	1374.93	− 5.18	− 5.73	− 11.21
Forest	714.39	689.81	680.59	− 3.56	− 1.35	− 4.96
Sand	87.67	116.47	93.27	24.72	− 24.87	6.00
Water	84.88	77.81	89.64	− 9.08	13.19	5.31

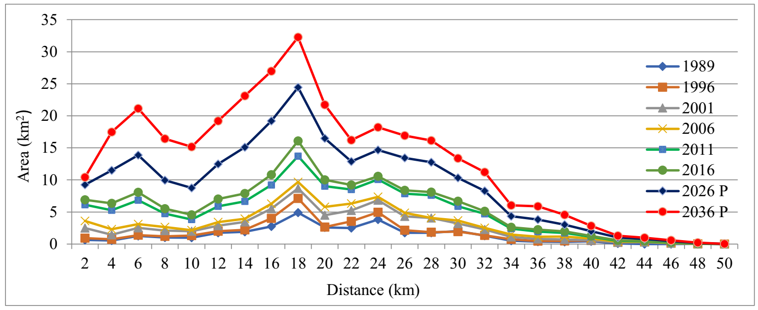


Fig. 5 Urban extent and growth from the assumed center outwards

Discussion

Continued growth of urban sprawl driven by increasing population is predicted for the developing countries of the South Asian region (UNDESA 2014). Previous studies (Corner et al. 2014; Dewan and Yamaguchi 2009; Dewan 2013; Sahana et al. 2018; Shafizadeh Moghadam and Helbich 2013) have examined urbanization-driven LULC changes in various mega-cities in this region. Many have used remote sensing and GIS tools to evaluate LULC, to produce simulation models, and to evaluate and predict future change for

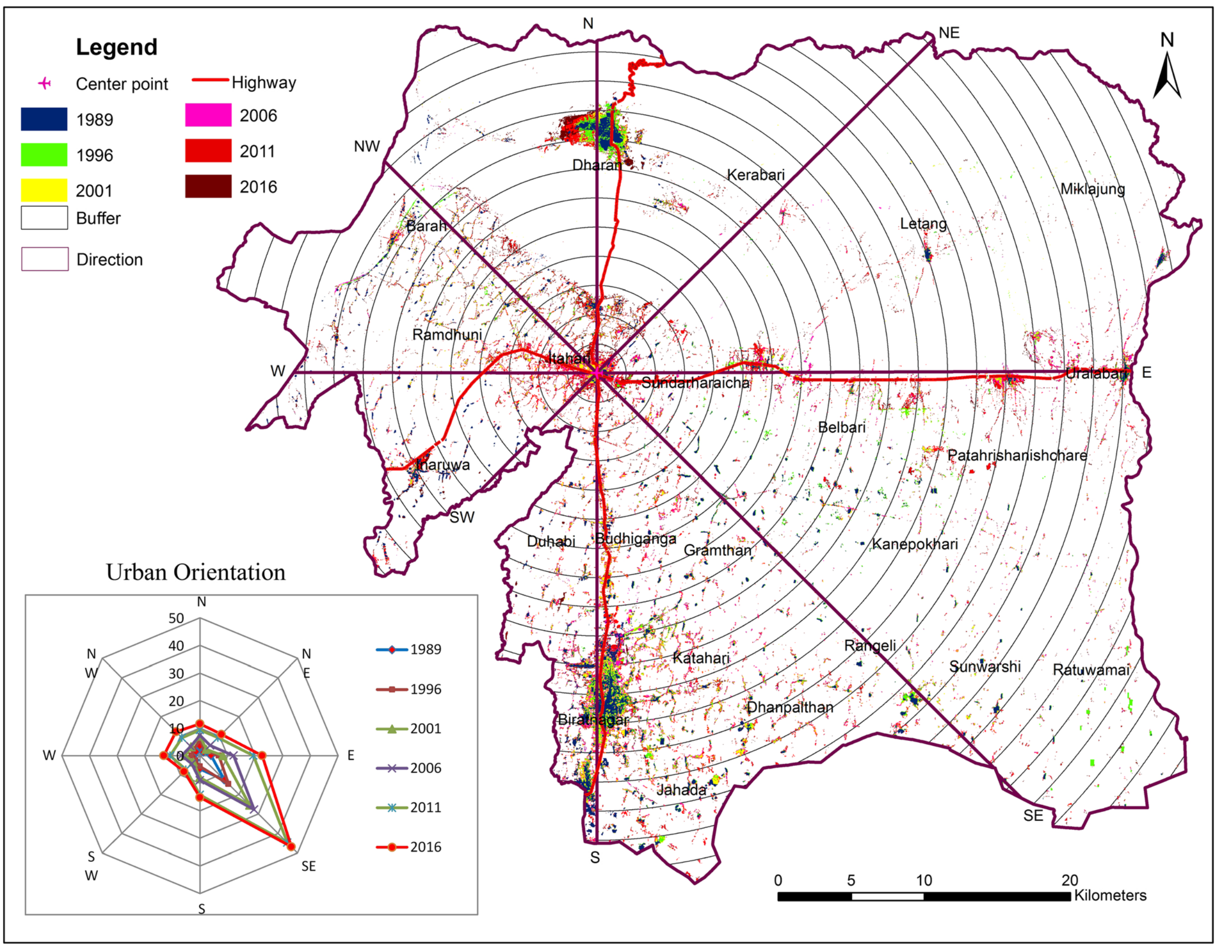


Fig. 6 Ring-based map of the study area

many of these cities including Mumbai (Shafizadeh Moghadam and Helbich 2013), Dhaka (Corner et al. 2014; Dewan 2013), Kolkata (Sahana et al. 2018), Shanghai (Han et al. 2009), and Foshan (Han and Jia 2017). Our results confirm what these previous studies observed and predicted gradual spatiotemporal urban expansion and continuing urban growth in cities and other urban areas in the South Asian region.

Major urban hotspots and surrounding areas are always influenced by human-induced LULC change (Ouyang et al. 2016). Ring-based analysis is generally used to identify more precisely the spatial location of urban expansion in urban centers (Jiao 2015; Rimal et al. 2017a; Shi et al. 2016; Wu et al. 2013; Zhang et al. 2016). Our ring-based analysis explored urban expansion based on landscape orientation and direction from the assumed center, which in this study is the Itahari sub-metropolitan city. The city is assumed as the center (Fig. 6) mainly due to three reasons: (a) it lies as the juncture of the east-west and north-south highways, the former extending from the eastern to western borders of the country and the latter, the Koshi highway, being the major road network connecting the hill districts in eastern Nepal; (b) it is the major hub for the socio-economic activities in the study area for the last two decades; and (c) it is the core area for settling migrants. Ring-based spatial analysis (Yin et al. 2011) of the study area portrays that higher urban expansion has occurred within 18-km distance from the assumed center (Fig. 5 and Fig. 6). This is because of the integration of major urban centers: Itahari sub-metropolitan city (the assumed center itself), Biratnagar metropolitan city in the south, and Dharan sub-metropolitan city in the north. The peripheral areas are newly urbanized and the density of previous settlements has increased. New urban centers are emerging adjacent to east-west highway (MOUD 2015) and the Koshi highway (Fig. 6).

Urbanization in Nepal is mainly driven by population growth, political decisions, public service accessibility, land market prices, economic opportunities, and government plans and policies (Muzzini and Gabriela 2013; Pradhan and Perera 2005; Thapa and Murayama 2010). Urban expansion is expected to continue to grow in the city outskirts and the peripheral areas for various socio-economic reasons with Urlabari, Belbari, Letang, Pathari, and Inaruwa being the emerging cities of the region. Higher expansion is expected to occur towards E-SE and S-ES directions (Fig. 6). Simulation analysis predicts that the urban area of 46.80 km^2 area of the SE-S sector in 2016 will expand to 93 km^2 by 2036. Meanwhile, the urban area of 22.53 km^2 in the E-SE direction in 2016 will more than double to 55.62 km^2 by 2036 (Fig. 4c and d).

Without well-defined plans/policies and effective public administrations, urbanization generally results in unmanaged urban sprawl (Rimal et al. 2018d). High population (Güneralp and Seto 2013) concentration fosters the exploitation of natural resources and causes complex changes in LULC and overall natural environment (Zeba et al. 2017). For instance, increasing population and urbanization can cause increased food consumption (FAO 2018). Densely populated urban areas demand plentiful natural resources and food (Jacoby 2001) and so, when prime farm land decreases (Seto et al. 2011), forests degenerate, surface water quality becomes degraded impacting aquatic life (Alqurashi et al. 2016; Li and Ma 2014; Liu et al. 2016; Pires et al. 2015). Dense urban areas increase the risk of formation of urban heat island and other natural hazards (Dewan et al. 2012; Paudel et al. 2016; Rahman 2016; Rimal et al. 2017b). In the case of our study area, the northern Churiya (Siwalik) region is exploited for sand and extraction requires for construction activities in urban development and such extraction could lead to widespread sediment accumulation in farmland downstream due to floods during the monsoon season (Rijal et al. 2018). Our simulations indicate that cultivated land in the periphery of major cities such as Biratnagar, Dharan, and Itahari are likely to decline. This could result in widespread environmental disequilibrium, loss of farm land, and in problems of future food security. Urban expansion and related development activities could also result in the loss of biodiversity and ecosystem services as seen in other regions of Nepal (Sharma et al. 2019; Sharma et al. 2018). The government proposes to develop 10 modern cities in the "Postal highway zone", which includes some part of the current study area (https://www.onlinekhabar.com/2018/12/724021). For this, it will need to have appropriate planning prior to the development of these new city centers since unmanaged and unplanned development activities (Bhattarai and Conway 2010) tend to result in the fragmentation in associated land uses and decline in prime cultivated land.

Conclusion

Our study analyzed the spatiotemporal change in LULC of eastern Tarai districts of Nepal during 1989–2016 and predicted the urban expansion scenario by 2026 and 2036 using the CA-Markov model. The spatial extent of urban/built-up area in the region was found to have aggressively increased from 29.20 km^2 in 1989 to 140.10 km^2 in 2016 and is expected to cover 318 km^2 by 2036, strongly corroborating the over exploitation of cultivated land. The cultivated land decline is likely to continue in the future. According to the prediction analysis, the current trend of erratic urbanization will continue and expand to 229.05 km^2 (8.95%) and 318.51 km^2 (12.45%) by 2026 and 2036, respectively, with the corresponding declines in cultivated land to 1453.83 km^2 (56.86%) and 1374.93 km^2 (53.77%) over the same years. Urban area expanded with the average annual growth rate of 6.36% during 1996–2016; however, the rate is expected to increase to 11.96% during 2016–2036. These findings suggest that this will result in increasing food insecurity and environmental degradation particularly since population growth is highly predictable. There is limited implementation of planning and policy to preserve cropland and urban expansion. Similarly, some of the existing/emerging settlements and prime farm lands are at the risk of flood hazard/inundation (Rijal et al. 2018; Rimal et al. 2018b). This indicates that there is an urgent need for sustainable urban planning and preservation of prime farm lands. Our findings are essential data for planners and policymakers to use in making rational decisions mainly due to two reasons: (a) obtaining spatiotemporal change is strongly essential for effective land management and sustainable rural-urban resilience and (b) our projections indicate the spatiotemporal locations of future urban sprawl and associated LULC. Our study affirms the value of the CA-Markov model as a tool for projecting future LULC changes as the evaluation showed the satisfactory values of Kno (0.89), Kstandard (0.84), and Klocation (0.89) which verify the accuracy of the model.

References

Al-Quraishi, A. (2013). *Sand dunes monitoring using remote sensing and GIS techniques for some sites in Iraq* (Vol. 8762). https://doi.org/10.1117/12.2019735.

Alqurashi, A., Kumar, L., & Sinha, P. (2016). Urban land cover change modelling using time-series satellite images: a case study of urban growth in five cities of Saudi Arabia. *Remote Sensing, 8*, 838. https://doi.org/10.3390/rs8100838.

Araya, Y. H., & Cabral, P. (2010). Analysis and modeling of urban land cover change in Setúbal and Sesimbra, Portugal. *Remote Sensing, 2*, 1549–1563. https://doi.org/10.3390/rs2061549.

Asma, G., Cyril De, R., & Herman, A. (2017). Urban development modelling: a survey. In F. Sami & M. Khaoula (Eds.), *Handbook of research on geographic information systems applications and advancements* (pp. 96–124). Hershey: IGI Global. https://doi.org/10.4018/978-1-5225-0937-0.ch004.

Batty, M. X. Y. (2005). *Urban growth using cellular automata models* (First ed.). New York Street Redlands: ESRI Press.

Bhattarai, K., & Conway, D. (2010). Urban vulnerabilities in the Kathmandu Valley, Nepal: visualizations of human/hazard interactions. *Journal of Geographic Information System, 02*(02), 20. https://doi.org/10.4236/jgis.2010.22012.

Campbell, J. B. (1996). *Introduction to remote sensing*. New York: The Guilford Press.

CBS. (2014). *Population monograph of Nepal*. Kathmandu: National Planning Commission Secretariat, Central Bureau of Statistics (CBS).

Cholhyok, K., Zhang, Y., Paudel, B., Liu, L., Wang, Z., & Li, R. (2018). *Exploring the factors driving changes in farmland within the Tumen/Tuman River Basin* (Vol. 7). https://doi.org/10.3390/ijgi7090352.

Clarke, K. C. (2018). Land use change modeling with SLEUTH: improving calibration with a genetic algorithm. In M. T. Camacho Olmedo, M. Paegelow, J.-F. Mas, & F. Escobar (Eds.), *Geomatic approaches for modeling land change scenarios* (pp. 139–161). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-319-60801-3_8.

Corner, R. J., Dewan, A. M., & Chakma, S. (2014). Monitoring and prediction of land-use and land-cover (LULC) change. In A. Dewan & R. Corner (Eds.), *Dhaka megacity: geospatial perspectives on urbanisation, environment and health* (pp. 75–97). Dordrecht: Springer Netherlands. https://doi.org/10.1007/978-94-007-6735-5_5.

Dewan AMCRJ (2013) Spatiotemporal analysis of urban growth, sprawl and structure. In Dhaka megacity, geospatial perspectives on urbanization, environment and health.

Dewan, A. M., & Yamaguchi, Y. (2009). Land use and land cover change in Greater Dhaka, Bangladesh: using remote sensing to promote sustainable urbanization. *Applied Geography, 29*, 390–401. https://doi.org/10.1016/j.apgeog.2008.12.005.

Dewan, A. M., Kabir, M. H., Nahar, K., & Rahman, M. Z. (2012). Urbanisation and environmental degradation in Dhaka Metropolitan Area of Bangladesh. *International Journal of Environment and Sustainable Development, 11*, 118–147. https://doi.org/10.1504/ijesd.2012.049178.

FAO. (2018). *The state of food security and nutrition in the world 2018.building climate resilience for food security and nutrition*. Rome: Food and Agriculture Organization (FAO) of the United Nations.

Feng, Y., Lu, D., Moran, E., Dutra, L., Calvi, M., & de Oliveira, M. (2017). Examining spatial distribution and dynamic change of urban land covers in the Brazilian Amazon using multitemporal multisensor high spatial resolution satellite imagery. *Remote Sensing, 9*, 381.

Fisk, D. (2012). The urban challenge. *Science, 336*, 1396–1397. https://doi.org/10.1126/science.1223952.

GoN. (2017). *Administrative map of Nepal. Government of Nepal (GoN)*. Kathmandu: Srvey Department, Min Bhawan.

Güneralp, B., & Seto, K. C. (2013). Futures of global urban expansion: uncertainties and implications for biodiversity conservation. *Environmental Research Letters, 8*, 014025. https://doi.org/10.1088/1748-9326/8/1/014025.

Han, Y., & Jia, H. (2017). Simulating the spatial dynamics of urban growth with an integrated modeling approach: a case study of Foshan, China. *Ecological Modelling, 353*, 107–116. https://doi.org/10.1016/j.ecolmodel.2016.04.005.

Han, J., Hayashi, Y., Cao, X., & Imura, H. (2009). Application of an integrated system dynamics and cellular automata model for urban growth assessment: a case study of Shanghai, China. *Landscape and Urban Planning, 91*, 133–141. https://doi.org/10.1016/j.landurbplan.2008.12.002.

Jacoby, K. (2001). *World ecological degradation: accumulation, urbanization, and deforestation, 3000 B.C–2000 A.D History: reviews of new books* (Vol. 30, pp. 38–38). https://doi.org/10.1080/03612759.2001.10525983.

Jiao, L. (2015). Urban land density function: a new method to characterize urban expansion. *Landscape and Urban Planning, 139*, 26–39. https://doi.org/10.1016/j.landurbplan.2015.02.017.

Jokar Arsanjani, J., Helbich, M., Kainz, W., & Darvishi Boloorani, A. (2013). Integration of logistic regression, Markov chain and cellular automata models to simulate urban expansion. *International Journal of Applied Earth Observation and Geoinformation, 21*, 265–275. https://doi.org/10.1016/j.jag.2011.12.014.

Julius Oluranti, O. (2018). *Geospatial analysis of land cover change and urban sprawl trend in Akure Region, Nigeria* (Vol. 3). https://doi.org/10.15406/mojes.2018.03.00062.

Kaplan, D. H., Wheeler, J. O., Holloway, S. R., & Hodler, T. W. (2004). *Urban geography*. Wiley.

Keshtkar, H., & Voigt, W. (2015). A spatiotemporal analysis of landscape change using an integrated Markov chain and cellular automata models. *Modeling Earth Systems and Environment, 2*. https://doi.org/10.1007/s40808-015-0068-4.

Keshtkar, H., & Voigt, W. (2016). Potential impacts of climate and landscape fragmentation changes on plant distributions: coupling multi-temporal satellite imagery with GIS-based cellular automata model. *Ecological Informatics, 32*, 145–155. https://doi.org/10.1016/j.ecoinf.2016.02.002.

Keshtkar, H., Voigt, W., & Alizadeh, E. (2017). Land-cover classification and analysis of change using machine-learning classifiers and multi-temporal remote sensing imagery. *Arabian Journal of Geosciences, 10*, 1–15. https://doi.org/10.1007/s12517-017-2899-y.

Khudair, B., Sameer Sadeq, N., & Sameer mahmoud, R. (2018). *Determining and predicting the water demand dynamic system model mapping urban crawling and monitoring using remote sensing techniques and GIS* (Vol. 24). https://doi.org/10.31026/j.eng.2018.06.08.

Li, S., & Ma, Y. (2014). Urbanization, economic development and environmental change. *sustainability, 6*, 5143–5161. https://doi.org/10.3390/su6085143.

Li, X., Zhou, W., & Ouyang, Z. (2013). Forty years of urban expansion in Beijing: what is the relative importance of physical, socioeconomic, and neighborhood factors? *Applied Geography, 38*, 1–10. https://doi.org/10.1016/j.apgeog.2012.11.004.

Liu Z, He C, Wu J (2016) General spatiotemporal patterns of urbanization: an examination of 16 world cities sustainability 8:41 https://doi.org/10.3390/su8010041.

Markus, S. (2017). Spatial and spatiotemporal data types as a foundation for representing space-time data in GIS. In F. Sami & M. Khaoula (Eds.), *Handbook of research on geographic information systems applications and advancements* (pp. 1–28). Hershey: IGI Global. https://doi.org/10.4018/978-1-5225-0937-0.ch001.

Meiyappan, P., Roy, P. S., Sharma, Y., Ramachandran, R. M., Joshi, P. K., DeFries, R. S., & Jain, A. K. (2017). Dynamics and determinants of land change in India: integrating satellite data with village socioeconomics. *Regional Environmental Change, 17*, 753–766. https://doi.org/10.1007/s10113-016-1068-2.

MoFALD. (2017). *Local level reconstruction report*. Kathmandu: Ministry of Federal Affairs and Local Development (MoFALD), Nepal Government.

MOUD. (2015). *National urban development strategy (NUDS) 2015*. Kathmandu: Government of Nepal, Ministry of Urban Development.

Mountjoy, A. B. (1978). Urbanisation in the third world. In A. B. Mountjoy (Ed.), *The third world: problems and perspectives* (pp. 102–111). London: Macmillan Education UK. https://doi.org/10.1007/978-1-349-16030-3_10.

Muzzini, E., & Gabriela, A. (2013). *Urban growth and spatial transition in Nepal* (p. 20433). Washington DC: The World Bank, 1818 H Street NW.

Nagendra, H., Bai, X., Brondizio, E. S., & Lwasa, S. (2018). The urban south and the predicament of global sustainability. *Nature Sustainability, 1*, 341–349. https://doi.org/10.1038/s41893-018-0101-5.

Ouyang, Z., Fan, P., & Chen, J. (2016). Urban built-up areas in transitional economies of Southeast Asia: spatial extent and dynamics. *Remote Sensing, 8*, 819. https://doi.org/10.3390/rs8100819.

Paudel, B., Gao, J., Zhang, Y., Wu, X., Li, S., & Yan, J. (2016). Changes in cropland status and their driving factors in the Koshi River basin of the Central Himalayas, Nepal. *Sustainability, 8*, 933.

Pires, N. L., Muniz, D. H., Kisaka, T. B., Simplicio Nde, C., Bortoluzzi, L., Lima, J. E., & Oliveira-Filho, E. C. (2015). Impacts of the urbanization process on water quality of Brazilian savanna rivers: the case of Preto River in Formosa, Goias State, Brazil. *International Journal of Environmental Research and Public Health, 12*, 10671–10686. https://doi.org/10.3390/ijerph120910671.

Pontius, R. G., & Millones, M. (2011). Death to kappa: birth of quantity disagreement and allocation disagreement for accuracy assessment. *International Journal of Remote Sensing, 32*, 4407–4429. https://doi.org/10.1080/01431161.2011.552923.

Pradhan, P., & Perera, R. (2005). Urban growth and its impact on the livelihoods of Kathmandu Valley. In *Nepal*.

Rahman, M. (2016). Detection of land use/land cover changes and urban sprawl in Al-Khobar, Saudi Arabia: an analysis of multi-temporal remote sensing data. *ISPRS International Journal of Geo-Information, 5*, 15. https://doi.org/10.3390/ijgi5020015.

Rai, R., Zhang, Y., Paudel, B., Acharya, B., & Basnet, L. (2018). Land use and land cover dynamics and assessing the

ecosystem service values in the trans-boundary Gandaki River Basin. *Central Himalayas Sustainability, 10*, 3052.
Rijal, S., Rimal, B., & Sloan, S. (2018). Flood hazard mapping of a rapidly urbanizing city in the foothills (Birendranagar, Surkhet) of Nepal. *Land, 7*, 60. https://doi.org/10.3390/land7020060.
Rimal, B., Zhang, L., Fu, D., Kunwar, R., & Zhai, Y. (2017a). Monitoring urban growth and the Nepal earthquake 2015 for sustainability of Kathmandu Valley, Nepal. *Land, 6*, 1-23. https://doi.org/10.3390/land6020042.
Rimal, B., Zhang, L., Keshtkar, H., Wang, N., & Lin, Y. (2017b). Monitoring and modeling of spatiotemporal urban expansion and land-use/land-cover change using integrated Markov chain cellular automata model. *ISPRS International Journal of Geo-Information, 6*, 1–21. https://doi.org/10.3390/ijgi6090288.
Rimal, B., Zhang, L., Keshtkar, H., Haack, B., Rijal, S., & Zhang, P. (2018a). Land use/land cover dynamics and modeling of urban land expansion by the integration of cellular automata and Markov chain. *ISPRS International Journal of Geo-Information, 7*, 154. https://doi.org/10.3390/ijgi7040154.
Rimal, B., Zhang, L., Keshtkar, H., Sun, X., & Rijal, S. (2018b). Quantifying the spatiotemporal pattern of urban expansion and hazard and risk area identification in the Kaski District of Nepal. *Land, 7*, 37. https://doi.org/10.3390/land7010037.
Rimal, B., Zhang, L., & Rijal, S. (2018c). Crop cycles and crop land classification in Nepal using MODIS NDVI. *Remote Sensing in Earth Systems Sciences, 1*, 14–28. https://doi.org/10.1007/s41976-018-0002-4.
Rimal, B., Zhang, L., Stork, N., Sloan, S., & Rijal, S. (2018d). Urban expansion occurred at the expense of agricultural lands in the Tarai region of Nepal from 1989 to 2016. *Sustainability, 10*, 1341. https://doi.org/10.3390/su10051341.
Rodrigues, H., & Soares-Filho, B. (2018). A short presentation of Dinamica EGO. In M. T. Camacho Olmedo, M. Paegelow, J.-F. Mas, & F. Escobar (Eds.), *Geomatic approaches for modeling land change scenarios* (pp. 493–498). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-319-60801-3_35.
Sahana, M., Hong, H., & Sajjad, H. (2018). Analyzing urban spatial patterns and trend of urban growth using urban sprawl matrix: a study on Kolkata urban agglomeration, India. *Science of the Total Environment, 628-629*, 1557–1566. https://doi.org/10.1016/j.scitotenv.2018.02.170.
Seto, K. C., Fragkias, M., Guneralp. B., & Reilly, M. K. (2011). A meta-analysis of global urban land expansion. *PLoS One, 6*, e23777. https://doi.org/10.1371/journal.pone.0023777.g001.
Seto, K. C., Guneralp, B., & Hutyra, L. R. (2012). Global forecasts of urban expansion to 2030 and direct impacts on biodiversity and carbon pools. *Proceedings of the National Academy of Sciences of the United States of America, 109*, 16083–16088. https://doi.org/10.1073/pnas.1211658109.
Sexton, J. O., Song, X.-P., Huang, C., Channan, S., Baker, M. E., & Townshend, J. R. (2013). Urban growth of the Washington, D.C.–Baltimore, MD metropolitan region from 1984 to 2010 by annual, Landsat-based estimates of impervious cover. *Remote Sensing of Environment, 129*, 42–53. https://doi.org/10.1016/j.rse.2012.10.025.
Shafizadeh Moghadam, H., & Helbich, M. (2013). Spatiotemporal urbanization processes in the megacity of Mumbai, India: a Markov chains-cellular automata urban growth model. *Applied Geography, 40*, 140–149. https://doi.org/10.1016/j.apgeog.2013.01.009.
Sharma, R., Rimal, B., Stork, N., Baral, H., & Dhakal, M. (2018). Spatial assessment of the potential impact of infrastructure development on biodiversity conservation in lowland Nepal. *ISPRS International Journal of Geo-Information, 7*, 1-13. https://doi.org/10.3390/ijgi7090365.
Sharma R, Rimal B, Paudyal K, Baral H, Acharya RP, Ranpal S, Kandel P (2019) Impact of land cover change on ecosystem services in a tropical forested landscape *Resources, 8*, 1-13. https://doi.org/10.3390/resources8010018.
Shi, M., Xie, Y., & Cao, Q. (2016). Spatiotemporal changes in rural settlement land and rural population in the Middle Basin of the Heihe River, China. *Sustainability, 8*, 614. https://doi.org/10.3390/su8070614.
Sleeter, B. M., Wood, N. J., Soulard, C. E., & Wilson, T. S. (2017). Projecting community changes in hazard exposure to support long-term risk reduction: a case study of tsunami hazards in the U.S. Pacific Northwest. *International Journal of Disaster Risk Reduction, 22*, 10–22. https://doi.org/10.1016/j.ijdrr.2017.02.015.
Thapa, R. B., & Murayama, Y. (2010). Drivers of urban growth in the Kathmandu valley, Nepal: examining the efficacy of the analytic hierarchy process. *Applied Geography, 30*, 70–83. https://doi.org/10.1016/j.apgeog.2009.10.002.
Thapa, R. B., & Murayama, Y. (2012). Scenario based urban growth allocation in Kathmandu Valley, Nepal. *Landscape and Urban Planning, 105*, 140–148. https://doi.org/10.1016/j.landurbplan.2011.12.007.
Theobald, D. (2005). Landscape patterns of exurban growth in the USA from 1980 to 2020. *Ecology and Society, 10*.
Traore, A., Mawenda, J., & Komba, A. (2018). *Land-cover change analysis and simulation in Conakry (Guinea), using hybrid cellular-automata and Markov model* (Vol. 2). https://doi.org/10.3390/urbansci2020039.
Umar, B., & Indo, B. (2018). Revisiting urban theories: their impacts on the developing world's urbanization. In B. Umar & B. Indo (Eds.), *Urbanization and its impact on socio-economic growth in developing regions* (pp. 1–22). Hershey, PA, USA: IGI Global. https://doi.org/10.4018/978-1-5225-2659-9.ch001.
UNESCAP. (2015). *The state of Asian and Pacific Cities 2015*. Urban transformations shifting from quantity to quality. United Nations Economic and Social Commission for Asia and the Pacific.
UNDESA. (2014). *World urbanization prospects, the 2014 revision*. New York: United Nation, United Nations, Department of Economic and Social Affairs, Population Division.
UNDESA. (2017). *World population prospects the 2017 revision*. New York: United Nations,, United Nations, Department of Economic and Social Affairs, Population Division.
UNDESA. (2018). *World urbanization prospects: the 2018 revision*. United Nation Development of Economic and Social Affairs, United Nation.
Verburg, P. H. V. A. (2004). Projecting land use transitions at forest fringes in the Philippines at two spatial scales. *Landscape Ecology, 19*, 77–98.
Verburg, P. H., Ritsema van Eck, J. R., Nijs, d T C M., Dijst, M. J., & Schot, P. (2004). Determinants of land-use change patterns

in the Netherlands. *Environment and Planning B - Planning and Design, 31*, 125–150.

Verburg, P. H., Crossman, N., Ellis, E. C., Heinimann, A., Hostert, P., Mertz, O., Nagendra, H., Sikor, T., Erb, K. H., Golubiewski, N., Grau, R., Grove, M., Konaté, S., Meyfroidt, P., Parker, D. C., Chowdhury, R. R., Shibata, H., Thomson, A., & Zhen, L. (2015). Land system science and sustainable development of the earth system: a global land project perspective. *Anthropocene, 12*, 29–41. https://doi.org/10.1016/j.ancene.2015.09.004.

Wang, R., Derdouri, A., & Murayama, Y. (2018a). Spatiotemporal simulation of future land use/cover change scenarios in the Tokyo metropolitan area. *Sustainability, 10*, 2056.

Wang, R., Hou, H., & Murayama, Y. (2018b). *Scenario-based simulation of Tianjin City using a cellular automata–Markov model* (Vol. 10). https://doi.org/10.3390/su10082633.

Wu, J., Jenerette, G. D., Buyantuyev, A., & Redman, C. L. (2011). Quantifying spatiotemporal patterns of urbanization: the case of the two fastest growing metropolitan regions in the United States. *Ecological Complexity, 8*, 1–8. https://doi.org/10.1016/j.ecocom.2010.03.002.

Wu, H., Sun, Y., Shi, W., Chen, X., & Fu, D. (2013). Examining the satellite-detected urban land use spatial patterns using multidimensional fractal dimension indices. *Remote Sensing, 5*, 5152–5172. https://doi.org/10.3390/rs5105152.

Yadav SK, Borana SL, S.K. Parihara (2018) Mapping and assessment of LU-LC features of the Jodhpur city using geoinformatic techniques.

Yan, Y., Zhang, C., Hu, Y., & Kuang, W. (2015). Urban land-cover change and its impact on the ecosystem carbon storage in a dryland City. *Remote Sensing, 8*, 6. https://doi.org/10.3390/rs8010006.

Yin, J., Yin, Z., Zhong, H., Xu, S., Hu, X., Wang, J., & Wu, J. (2011). Monitoring urban expansion and land use/land cover changes of Shanghai metropolitan area during the transitional economy (1979-2009) in China. *Environmental Monitoring and Assessment, 177*, 609–621. https://doi.org/10.1007/s10661-010-1660-8.

Zeba, A. N., Yameogo, M. T., Tougouma, S. J., Kassie, D., & Fournet, F. (2017). Can urbanization, social and spatial disparities help to understand the rise of cardiometabolic risk factors in Bobo-Dioulasso? A study in a secondary city of Burkina Faso, West Africa. *International Journal of Environmental Research and Public Health, 14*. https://doi.org/10.3390/ijerph14040378.

Zhang, X. Q. (2016). The trends, promises and challenges of urbanisation in the world. *Habitat International, 54*, 241–252. https://doi.org/10.1016/j.habitatint.2015.11.018.

Zhang, Z., Li, N., Wang, X., Liu, F., & Yang, L. (2016). A comparative study of urban expansion in Beijing, Tianjin and Tangshan from the 1970s to 2013. *Remote Sensing, 8*, 496.