Research article

Prediction of Land Use Change through the Cellular Automata-Markov Model: A Case Study of the Upper Sangkae River Basin in Cambodia

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Abstract The expansion of agricultural land and the diminishment of forest cover in Battambang Province (Cambodia) has been recently reported. At the same time, while forest cover has decreased, the amount of water resources in the river basin has been variable. The aim of the current study was to forecast land use change in the upper Sangkae River basin of Battambang Province by 2030. For this purpose, remote sensing and geographic information systems (GIS) methods were used to analyze satellite data from 2014 to 2018, using the generated maps as data input in the cellular automata (CA)-Markov model. We also integrated the CA-Markov model and GIS spatial analyst tools to assess what will most likely occur in the presence of policy intervention from land use development planning by 2030. Additionally, the model simulated actual and predicted land use in 2022 for accuracy assessment, using the Kappa Index of Agreement for confirmation. Based on the findings, the modeled scenario predicted the increase in built-up land and the decrease in the natural forest cover by 2030 in the absence of a land use policy. Additionally, the findings suggested that in the absence of a land use policy, forest cover will suffer from continued deforestation until forest loss reaches the protected area boundary. Conversely, in the presence of a land use policy, the model shows an increase in forest cover by 2030, even though some areas would be allocated under economic land concessions for industrial agriculture. Moreover, non-forest cover, such as farmlands and paddy fields, is not expected to decline, whereas built-up land is forecast to dramatically increase, with or without policy intervention. This study sheds light on the use of practical evaluation tools for governmental land use policies and development planning.

Keywords CA-Markov model, land use change, government land use planning, prediction

INTRODUCTION

Land use/land cover has been considered the main factor in changing the hydrological cycle since it directly influences evapotranspiration and soil moisture contents (Gupta et al., 2015). In this regard, significant land use changes in Battambang Province (Cambodia) have been recently reported. For example, previous research (Sourn et al., 2021) found a considerable increase in agricultural land, with a dramatic decrease in forest cover between 1998 and 2018. These changes were driven by population growth, economic growth, landmine clearance projects, and social and economic land concessions (SLCs and ELCs, respectively). Based on the Cambodia Land Law of 2001 (Open Development Cambodia), the term SLC refers to the social purpose of allowing beneficiaries to build residential constructions and/or cultivate land belonging to the state for their subsistence. The term ELC refers to the economic purpose of allowing beneficiaries to clear the land for industrial and agricultural exploitation.

Understanding land use change has become an increasing matter of interest and concern among landscape planners and environmentalists because it influenced the global environment (Subedi et al., 2013). Land use/land cover mapping derived from remotely sensed data has long been an area of focus for many researchers (Civco et al., 2002; Araya and Cabral, 2010). Meanwhile, recent advancements in geographic information systems (GIS) and remote sensing tools/methods have enabled researchers to effectively model land use change (Araya and Cabral, 2010).

In general, modeling land use dynamics is a complex process (Subedi et al., 2013), due to factors such as natural settings, society, economics, culture, politics, and legal aspects (Lambin, 1997). Various models for land use simulation and prediction have been used in GIS such as statistic, dynamic, and machine learning modeling (Aburas et al., 2019). Based on historical spatio-temporal data, the cellular automata (CA)-Markov module in IDIRISI software was first used in this study to simulate and predict future land use change, due to its widespread use by scholars to understand landscape change at the global level (Wang et al., 2021). It was also used to analyze the related effects and natural resource management strategies (Brown et al., 2000). However, this model did not consider land use policies and socio-economic factors (Subedi et al., 2013).

OBJECTIVE

Therefore, the present study examines the SLCs, ELCs, and potential areas for forest communities according to the local government's 2030 master plan (Open Development Cambodia). The primary objective is to integrate the CA-Markov model and GIS-based spatial analyst tools to enhance the predictive land-use change map.

METHODOLOGY

Study Area

The study focused on the upper Sangkae River basin, situated in Battambang Province (the largest agricultural area in Cambodia), with a total drainage area of 3,062 km^2 (Vanna et al., 2020) (Fig. 1). The elevation ranges from 13 to 1,400 meters above sea level. Based on Mekong River Commission (MRC) land use data in 2010, 53.13% of land use within this basin was covered by forest, followed by agriculture at 44.41%, built-up land at 2.03%, and water bodies at 0.44%. More than one million people live in this province, with an annual population growth rate of 2.28% (Hagenlocher et al., 2016). Meanwhile, human activities have been affected in this watershed by landmine clearance and explosive remnants of war projects, and land concessions (Sourn et al., 2021).

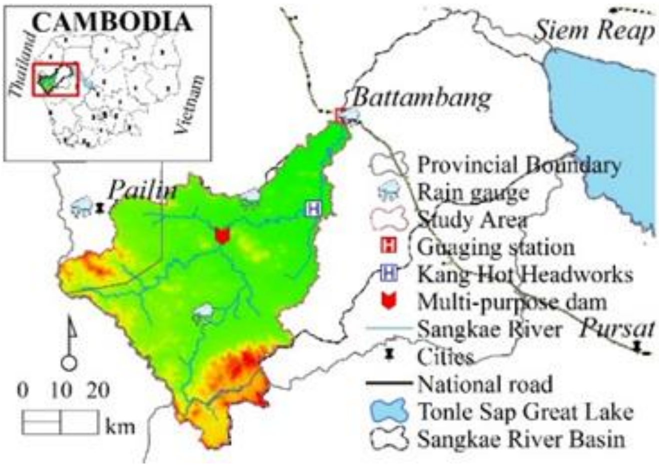

Fig. 1 Map of the study area

Data Input and Image Classification

Freely available Landsat 8 (Path 127-128, Row 51) images in 2014, 2018, and 2022 were acquired from the U.S. Geological Survey (https://earthexplorer.usgs.gov/). The images were mosaicked and composited using Bands 1-7 and projected in UTM 48N using ArcGIS 10.5. Due to prior knowledge of the Sangkae River basin, the images were classified by hard supervised classification, a popular algorithm of maximum likelihood based on signature files (Rawat and Kumar, 2015). According to the user's knowledge, a signature was processed by using the on-screen digitizing feature to create 5–12 vector files of the training site for each class. Land cover was identified, following MRC land use-2010 and satellite imagery, while land use was aggregated into five major classes: forest cover, farmlands, paddy fields, water bodies, and built-up areas. The stratified randoms of more than 500 points were created for each image using the Create Accuracy Assessment Points tool in ArcGIS. They were then manually checked and compared by using existing land use and the Google Earth Engine, as reference data. The overall accuracy and Kappa coefficient (Table 1) of the classified images were larger than 95% and 0.90, respectively.

Table 1 Accuracy assessment of image classification

Year	Overall accuracy	Kappa coefficient
LULC2022	95.06	0.92
LULC2018	95.40	0.94
LULC2014	96.00	0.95

Land Use Change Modeling and Prediction Process

In this study, three land use maps (2014, 2018, and 2022) were converted into ASCII files and then imported into IDIRISI software for land use change simulation and prediction. First, land use predictions in 2022 and 2030 were performed with the CA-Markov model (Eastman and Toledano, 2018) by inputting suitability maps, transition areas, and a transition probability matrix, all computed from the Markov chain analysis of the 2014 and 2018 images. Second, the 2018 image was set as the base map. Third, the VALIDATE module was used to assess the model's validity, which was confirmed by the statistical Kappa Index of Agreement (KIA). Fourth, the predicted land use in 2030 was generated by using the projected transition probability matrix derived from the simple powering of the base matrix (Takada et al., 2010). Finally, according to the presence of a future land use policy, another land use map was created by overlaying the development areas onto the predicted land use map in 2030.

The Markov and CA-Markov Models

The Markov model is a convenient tool for simulating land use/land cover change when variations in the landscape are difficult to describe (Kumar et al., 2014). Specifically, it depicts land use/land cover change from one period to another and uses it as a basis for predicting future changes. Table 2 presents the conversions of land use from one class to another for the 2014–2018 study period. The CA-Markov model combines the cellular automata-Markov chain and the multi-criteria/objective procedures for land use/land cover prediction (Eastman and Toledano, 2018). In particular, it allocates land based on the suitability of the land for end covers (along with a cellular automaton rule) to promote spatial contiguity (Eastman and Toledano, 2018). In addition, by using the Markov chain analysis outputs, especially the transition area file, the CA-Markov model applies a contiguity filter to grow land use from one time to a later time.

Table 2 Transition probability matrix from 2014 to 2018

Land use classes	Forest cover	Farmlands	Built-up land	Paddy fields	Waterbody
Forest cover	0.7435	0.2510	0.0005	0.0005	0.0045
Farmlands	0.1557	0.7503	0.0162	0.0549	0.0229
Built-up land	0.0014	0.2035	0.7666	0.0251	0.0034
Paddy fields	0.0225	0.2921	0.0003	0.6851	0.0000
Waterbody	0.0710	0.1909	0.0140	0.0019	0.7222

Regarding the suitability for predictive land use, it refers to the suitability of a cell for particular land use (Eastman and Toledano, 2018). Normally, suitability images are constructed with multi-criteria evaluation, a common method for assessing/aggregating the "constraint and factor" criteria. Constraints are usually represented as a Boolean image (0 and 1), while factors define some degree of suitability for all geographic regions. In this study, the factors were empirically developed by using the underlying land use change dynamics between 2014 and 2018.

Additionally, various factors, such as proximity to roads, water, canals, and existing land use were generated and standardized on a continuous scale of 0 (least suitable) to 255 (most suitable), using a fuzzy module. The factors of each land use class were then aggregated by employing pairwise comparison associated with the analytical hierarchy process in the weighted linear combination method. For more information on the Markov and CA-Markov models, see references (Subedi et al., 2013; Wang et al., 2021; Eastman, 2012; Hamad et al., 2018).

RESULTS AND DISCUSSION

Accuracy Assessment of the CA-Markov Model

Validation of the model is an essential pre-condition for research that predicts land use/land cover changes (Wang et al., 2021). The model validation in this study was achieved by simulating actual and predicted land use images in 2022, based on known land use in 2014 and 2018, and a KIA statistics-based assessment. According to Fig. 2, the actual and predicted land uses in 2022 are similar, except for the forest cover class, due to the map accuracy during image classification. In addition, the Kappa is 1 when the observed agreement is perfect, or 0 when the observed agreement is equal to the expected agreement (Pontius, 2022). The statistics derived from the VALIDATE module in IDIRISI software show that the Kappas for no information (Kno = 0.94), for location (Klocation = 0.94), for quantity (Kquantity = 0.94), and for standard (Kstandard = 0.92) were larger at 0.90 (Wang et al., 2021). Thus, the model was deemed valid and reliable for land use change projection.

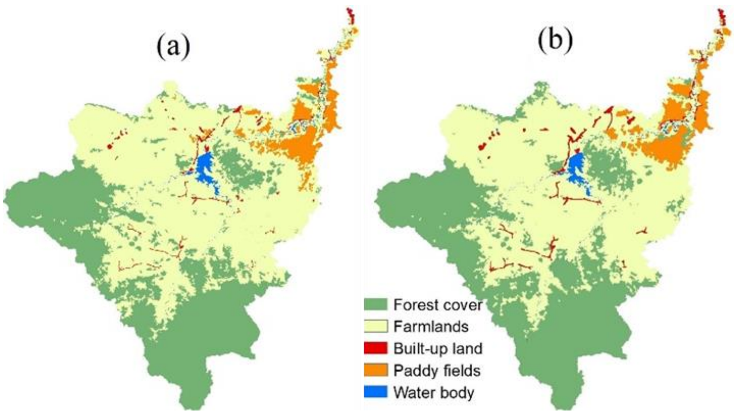

Fig. 2 The comparison of actual (a) and predicted (b) land uses in 2022

Prediction of Future Land Use

The land use prediction maps for 2030 are shown in Figs. 3(a) and 3(b). Specifically, the model scenario without a land use policy (Figure 3(a)) predicted that the farmlands will cover 52.12% of the total area of the upper Sangkae River basin, followed by forest cover (38.42%), paddy fields (6.69%), built-up land (1.82%), and water bodies (0.95%) (Table 3). Additionally, forest cover and farmlands are expected to decrease in area by 2030, compared to the predicted land use in 2022 (Table 3). However, this decrease will contribute to an increase in built-up land by 0.22%. It should be noted that the decline of forest cover in the study area has been observed over the past few decades. According to previous research (Sourn et al., 2021), deforestation was observed from 1998 to 2013. Up to 2018, forest cover was mostly stable in mountainous areas, especially naturally protected areas such as the Phnom Samkos Wildlife Sanctuary and the Samlot Multiple Use Area. The expansion of agricultural land in the upper Sangkae River basin will most likely reach these protected areas, reflecting the minor decline in forest cover predicted by the model.

With the presence of a land use development policy, the land use map in 2030 was achieved (Fig. 3(b)). If land use planning succeeds, then the positive impact on the natural forest cover in this basin can be seen in an increase in reforestation by 2030. In this case, our predicted land use shows that forest cover and built-up land of high and low population density increase by 0.78%, 0.20%, and 100%, respectively. Moreover, forest cover is predicted to increase, even though some areas at the upstream part of the river basin have been offered and allocated under ELCs. Nevertheless, the farmlands and paddy fields will decrease by 3.05% and 0.02%, respectively. Field surveys of current land use in mountain areas confirm that natural forests, even in protected areas, are being cut and burned to expand agricultural land. Therefore, it is predicted that deforestation will continue in the absence of effective land use policies. The land use policy here, however, is the planning of afforestation for forest communities by local governments. This policy is believed to help increase forest cover in the future.

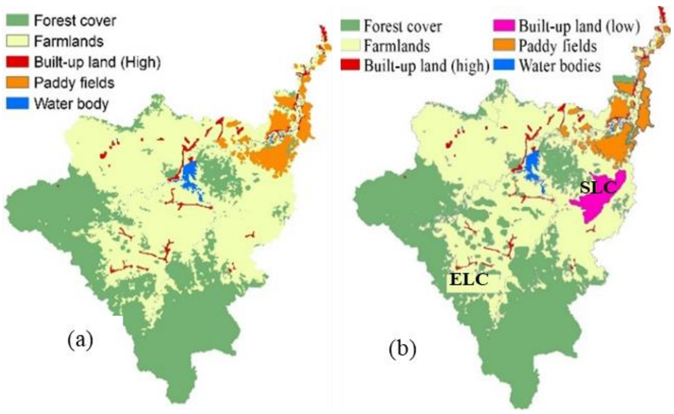

Fig. 3 The predicted land use in 2030

Overall, these decreases and increases are the result of government policies on land allocation. For instance, land use changes from farmlands to the built-up area of low population density appear as a new land use class. In this case, the land was allocated under SLCs. Meanwhile, the built-up area's expansion is expected to increase, due to the increase in the number of new marriages and residential development plans. Furthermore, there will be a slight decline in paddy fields, while water bodies will remain stable from 2018 to 2030.

Table 3 Predicted land use in 2030

Land use classes	Predicted LU2022		Without a land use policy: Predicted LU 2030		Without a land use policy: Rate of changes	With a land use policy: Predicted LU 2030		With a land use policy: Rate of changes
	Area (ha)	Area (%)	Area (ha)	Area (%)	(%)	Area (ha)	Area (%)	(%)
Forest cover	118,132.18	38.61	117,678.13	38.42	−0.19	120,619.33	39.39	0.78
Farmlands	159,732.80	52.18	159,570.39	52.12	−0.06	150,436.29	49.14	−3.05
Built-up land (high density)	4,914.26	1.61	5,579.82	1.82	0.22	5,538.65	1.81	0.20
Built-up land (low-density)	-	-	-	-	-	6,386.96	2.09	100.00
Paddy fields	20,360.63	6.65	20,477.64	6.69	0.03	20,311.63	6.63	−0.02
Water bodies	2,922.47	0.95	2,909.35	0.95	0.00	2,922.47	0.95	0.00
Total	306,215.34	-	306,215.34	-	-	306,215.34	-	-

Based on the guidelines from the Ministry of Land Management, Urban Planning, and Construction, 6,386 hectares (built-up land with low population density) of state land in the Samlot district of Battambang Province and its shared border with the Koh Krala district were converted into SLCs for the poor and retired soldiers. Specifically, these individuals were legally authorized to occupy one hectare of land with one house. This project was implemented under the Battambang Provincial Administration. Conversely, according to the Sub-degree on Reclassification of State Permanent Forest Reserve and Granting of ELCs for agro-industry investment in 2009 (Open Development Cambodia), 5,200 hectares of ELCs (Fig. 3(b)) in the Samlot district were converted from forest for development purposes (e.g., rubber plantations). However, we found that this zoning area only experienced tree cutting.In this study, the objective influences on land use patterns under the local government's land use development plan were successfully predicted by using the CA-Markov model. This model was effective because the land use planning focused on built-up land with low population density and farmland zoning. However, there are still the challenges of predicting land use change when considering human activities (e.g., commercial and/or urban development) and investments in land use development policies.

CONCLUSION

This study was the first attempt to predict future land use change and the effects of governmental land use planning in the upper Sangkae River basin of Cambodia. Land use prediction has become a critical issue, due to the uncertainty of land use policies and the capacity of available models. However, spatiotemporal land use dynamics through the CA-Markov model confirmed that it is a valuable tool for simulating and predicting future changes in the landscape. Moreover, the limitations of this model were fulfilled with assistance from ArcGIS tools. It is hoped that our results will not only be used to assess the impact of future land use changes on the hydrologic environment but also be integrated with climate change prediction models to contribute to future water demand projections.

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