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Updating and backdating analyses for mitigating uncertainties in land change modeling: A case study of the Ci Kapundung upper water catchment area, Java Island, Indonesia

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In developing countries, data gaps are common and lead to uncertainties in land cover change analysis. This study demonstrates how to mitigate uncertainties in modeling land change in the Ci Kapundung upper water catchment area by comparing the outcomes of two simulation phases. A conventional cellular automata (CA)–Markov model was complemented with a multilayer perceptron (MLP) to project future land cover maps in the study area. The CA–Markov–MLP model results in high uncertainties in forested sites where a data gap is apparent in the input data (land cover maps and driver variables) and parameters. The results show that the model accuracy is improved from 47.90% in the first phase to 81.36% in the second phase. Both first and second phases integrate six demographic-economic and environmental drivers in the modeling, but the second phase also incorporates an updating and backdating analysis to revise the base-maps. This study suggests that uncertainties can be mitigated by linking such base-map revision process with the updating and backdating analyses using remote sensing datasets retrieved at different times.

Keywords: land cover change; cellular automata; CA–Markov; multilayer perceptron; uncertainty

Introduction

Land cover change is a dynamic process (van Vliet *et al.* 2016) that is influenced by endogenous and exogenous variables (Baker 1989). The alteration can be analyzed using models (Verburg *et al.* 2004), where results can be affected by uncertainties in input data and model parameters (Verburg *et al.* 2013, Brown *et al.* 2014). According to Refsgaard *et al.* (2007), uncertainty refers to the degree of confidence in the modeling outcomes, as model accuracy is highly dependent on the quality of the input data. Methods to assess model

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uncertainties include, but are not limited to; expert elicitation, Monte Carlo analysis, scenario analysis, sensitivity analysis, and an uncertainty matrix (Refsgaard *et al.* 2007).

Land modeling can use different approaches and assumptions. Brown *et al.* (2014) proposed six categories of land change modeling approaches: machine learning, statistical, cellular, agent-based, sector-based economic, spatially disaggregated economic, and hybrid approaches. Other notable models include Markov chains and dynamic system models (Dang and Kawasaki 2016). Cellular automata (CA) perform well in the simulations of ecological and biogeophysical phenomena. However, this model is not always suitable for simulating land changes when human decisions are integrated into the models (Parker *et al.* 2003). Markov modeling, on the other hand, is an approach to simulate land changes based on historical trends (Brown *et al.* 2014) that excludes the spatial arrangement in the modeling process (Ghosh *et al.* 2017). The transition probabilities over time are calculated (Brown *et al.* 2014) and but are assumed to be stationary in most applications of the Markov chain (Baker 1989).

In 1995, Pijanowski first coupled artificial neural networks (ANNs) in machine learning with geographic information system (GIS) to simulate land-use alteration (Pijanowski *et al.* 2005). The multilayer perceptron (MLP) model is an example of one based on ANN (Gallant 1993). Machine learning algorithms generate nonlinear relationships between the patterns of land cover and explanatory variables (i.e., variables that cause the land cover change) in an iterative process (Pijanowski *et al.* 2002). In contrast to the linear regression model, machine learning does not require specific assumptions with mathematical equations to show the relationships between two patterns (Brown *et al.* 2014).

Uncertainties in land change modeling lead to difficulties in predicting changes using traditional methods (Ghosh *et al.* 2017). The integration of different models was proposed to simulate the complexity of land changes (Dang and Kawasaki, 2016). Hybrid modeling integrates different conceptual frameworks, theories, and empirical observations into a system. It offers an opportunity for modelers to select modeling procedures based on practical requirements (Brown *et al.* 2014).

Meta-studies on twenty existing research projects that employed the integrated CA–Markov–MLP model (2011-2020) were identified from the ISI Web of Science. Four of these studies were conducted in forested sites (Mirici *et al.* 2018, Nery *et al.* 2019, Yang *et al.* 2019, Gaur *et al.* 2020), but only one of them addressed the uncertainties in its modeling (Nery *et al.* 2019). Mirici *et al.* (2018) and Yang *et al.* (2019) suggest that an MLP in a hybrid land change model cannot produce a conversion potential for all types of landscapes in their case study areas. Gaur *et al.* 2020 concluded that MLP–Markov outperformed other models, such as linear regression–Markov, linear regression–CA–Markov, and MLP–CA–Markov, when these were utilized to simulate land cover maps in eastern India, but this finding cannot necessarily be generalized to other case studies. Uncertainties in the CA–Markov–MLP model were identified in a study in Australia (Nery *et al.* 2019) using the approach proposed by Pontius and Petrova (2010). However, there is no further explanation of how uncertainties have been mitigated to improve model accuracy.

This research aims to mitigate the uncertainties in the CA–Markov–MLP land change model using a case study based on a largely forested area within a tropical region. Such regions are challenging for land-change models, due to limited high-quality remote sensing data because of constant cloud cover and insufficient spatial data being available from local authorities. Thus the methodology presented in this research can be implemented in other studies with similar issues. Two main research questions are assessed in this paper: (1) What are the factors that led to uncertainties in the land change modeling of the study area? (2) How can the accuracy of the land change model be improved?

Case study

The case study is located in the Ci Kapundung upper water catchment area (102.86 km^2) in Bandung Basin, Indonesia (Figure 1). Six land cover types were distinguished during field surveys: developed areas, bare or cultivated land, mixed vegetation, conifers, broad-leaved vegetation, and water bodies.

Figure 1. The location of the study area - Bandung Basin in Indonesia (left), and land use types from a natural color composite image via satellite imagery of the Ci Kapundung upper water catchment area in 2015 (right). (Sources: AIRBUS DS 2015, BIG, OpenStreetMap, municipality government of Bandung City, Bandung Regency, and West Bandung Regency, Esri, USGS, NOAA)

Materials and methods

This study compares the results from two phases of land change modeling to show how uncertainties in the modeling of the case study area are identified and mitigated (Figure 2). High-resolution satellite imagery (SPOT 6) was used in the first phase of the study (LCM 1). Due to limited access to the data, only the available SPOT images from 2013 and 2015 were used to simulate the land cover composition and distribution in 2017. Based on the model validation outcomes, the second phase (LCM 2) was performed using base maps, which were developed from satellite imagery retrieved over a longer period of time using updating and backdating methods.

Figure 2. The two modeling phases employed for the case study area showing the workflow patterns

Land cover map development

Remote sensing data

SPOT images (6 m spatial resolution) were purchased from Airbus Defence and Space. Meanwhile, the Landsat imagery (30 m spatial resolution) was retrieved from the United States Geological Survey (USGS, www.usgs.gov/centers/eros) (Table 1).

Table 1 Remote sensing data used in the study

Auxiliary data

Data retrieved from field surveys, a forest map from Perhutani (a state-owned forest enterprise in Indonesia), and a visual interpretation of a World Imagery base map in ArcGIS (e.g., WorldView-2 and WorldView-3 imagery with 0.5 m and 0.31 m resolutions, respectively) were also used to develop and to validate the land cover maps. Data from OpenStreetMap were used to accurately map street networks in the case study area.

Image preprocessing and classification

Image preprocessing was conducted by performing an object masking procedure for cloud, cloud shadows, and water bodies and corrections on the satellite images. An object-based image analysis (OBIA) was used to reduce the "salt-and-pepper" effect, which appears in a map produced by the traditional pixel-based classification (Weih and Riggan 2010). Maximum likelihood (ML) was selected as the classifier in the classification process because of its robustness in most image-processing software (Lu and Weng 2007).

The updating and backdating approaches by Linke et al. (2009) were used to develop maps with multi-spatial resolutions using the SPOT and Landsat imageries in LCM 2 (Figure 3). A series of assumptions was applied, including the use of 2015 map from SPOT imagery as a base map due to the least cloud coverage compared with the 2013 and 2017 SPOT images

(Table 1), and the premise that unbuilt areas in later years were not built in previous years (Toure et al. 2018). In this study, the 2013 and 2015 SPOT images were used to develop a land cover map in circa 2015 (c.2015). The circa 2017 (c.2017) map was generated based on the 2015 map (updating process).

The information on the land cover in 2015 was also used to develop the circa 2000 (c.2000) map using the backdating method (Figure 3). First, the undeveloped areas in 2015 were assigned as unbuilt areas in c.2000. The remaining unbuilt area in c.2000 was defined based on the results of the normalized difference vegetation index (NDVI) analysis, which separate the non-vegetation classes (e.g., developed areas and bare land) from the vegetation class. Second, the OBIA was performed to identify two land cover types in the case study area (e.g., bare and cultivated lands and vegetation/woodland).

The map accuracy was calculated using five hundred accuracy ground control points assigned and randomly distributed within each class (Figure 4), in which the number of points was proportional to its relative area. Map validation was conducted using the mentioned auxiliary data because it was not feasible to survey several sites in the case study areas due to the steep slopes and lack of access. The confusion matrices were computed in all maps to derive an overall accuracy and a Kappa index of agreement between the classified land cover types and ground reference data.

Figure 3. Backdating and updating processes of land cover map development

Figure 4 (a–b). Ground control points for the c.2015 and c.2017 land cover maps in LCM 2

Land change modeling

Modeling structure

In this study, a predictive land change simulation (Börjeson *et al.* 2006) was conducted using the Land Change Modeler (LCM) module from Terrset. LCM applies an integrated CA and Markov model (CA–Markov) and an MLP neural network. Due to the small area, water bodies were excluded from the modeling. A constraint map was used in LCM to restrict future developments in forests and protected areas. The model was validated by comparing the 2017 land cover maps developed from satellite imagery with the simulated maps in the same year. A comparison between the observed and simulated land cover in LCM 2 within two years (e.g., 2015–2017) is sufficient for model validation (Verburg *et al.* 2004). Confusion matrices were used to assess model accuracy.

Environmental, demographic, and economic drivers

Six driver variables were assessed and used in the land change modeling (Figure 5). The six variables were divided into two groups, following the driving force categorization from Geist and Lambin (2002) and based on the origin of drivers. The first group is the economic and demographic drivers, which consist of "likelihood to change" (i.e., the probability of land cover in particular cells that would change based on the historical transitions), "distance from disturbance", and "population density". The first and the second drivers, which can be associated with urbanization, is an economic factor, whereas population density is a demographic factor (Geist and Lambin 2002). The second group contains the environmental drivers, including "elevation," "slopes," and "distance from streams".

Maps with elevation and the percentages of slope data were created from the digital elevation model (DEM) of the Indonesian Geospatial Agency. The raster was resampled from 8.34 m to 6 m to match the resolution of the land cover maps. River networks were generated using the hydrology toolbox in ArcGIS 10.7.1 based on DEM. Maps showing the distance from disturbance were derived from the existing land cover map in 2013 and c.2000 for LCM 1 and LCM 2, respectively, whereas the likelihood of land cover change was computed using all base maps. The spatial distribution of the population density in 2015 was retrieved from WorldPop (2014). The image shows the number of people per pixel (ppp) adjusted from the UN population division estimates. It has a resolution of 100 m, which was resampled to 6 m.

Figure 5. Maps showing "drivers of change" in the study area: (a) "likelihood to change" (2013–2015); (b) "distance from disturbance" (2013); (c) "likelihood to change" (2000–2015); (d) "distance from disturbance" (2000); (e) "population density" (2015); (f) "elevation"; (g) "slopes"; (h) "distance from streams"

Identification of uncertainty elements

In this study, uncertainty elements were identified in the land cover maps by referring to Foody (2002): sampling design, image processing, ground or reference data, spatial distribution error, and mixed pixels. Uncertainty factors in land change modeling were also conducted by assessing potential errors which affect the model accuracy.

Results

Results from the land cover map development

Figures 6(a–c) show the results from the OBIA for the individual 2013, 2015, and 2017 land cover maps used in LCM 1 with overall accuracies of 78.64%, 87.40%, and 86.40%, respectively. The outcome from the NDVI analysis shows the occurrence of mixed pixels when it was overlaid with higher-resolution images due to the lower spatial resolution of Landsat. The mixed pixels can also be observed in cloud and cloud shadow masking processes which cause such pixels cannot be directly masked. The c.2015 and c.2017 maps for LCM 2 have overall accuracies of 87.42% and 81.00%, respectively (Figures 6d-f). No accuracy assessment was conducted with the c.2000 land cover map because no ground reference data could be retrieved.

Figure 6 (a–c) OBIA results for the individual land cover maps in 2013, 2015, and 2017; (d–f) OBIA results for land cover maps in c.2000, c.2015, and c.2017.

Results from the land change modeling

Transition probability matrices

Table 2 shows the transition probability matrix (2013–2015) to simulate the 2017 land cover map in LCM 1. The transition probability matrix from 2000 to 2015 for projecting the land cover composition and distribution in 2017 in LCM 2 is presented in Table 3.

Table 2 Transition probability matrix (2013–2015) to predict the 2017 map in LCM 1

Table 3 Transition probability matrix (2000–2015) to predict the 2017 map in LCM 2

Prediction and validation of 2017 land cover maps

Several iterations of MLP were performed to generate transition potential maps using the combinations of driver variables in the two modeling phases (LCM 1 and LCM 2). The results indicate how specific drivers influence the model outputs (Table 4).

Table 4 MLP and model accuracies

The predicted 2017 maps with the environmental drivers in LCM 1 and demographic-economic drivers in LCM 2 show the different compositions and distributions of the projected land cover (Figures 7 and 8). More developed areas are expected to occur in 2017 in LCM 1 (23.10%) than in LCM 2 (18.09%). The newly developed areas are mostly located at the center of the watershed.

Figure 7 (a) Potential transition map in 2017; (b) projected 2017 map based on the status quo scenario (LCM 1)

Figure 8 (a) Potential transition map in 2017; (b) projected 2017 map based on the status quo scenario (LCM 2)

Factors leading to uncertainties in the land change modeling

The effect of uncertainties in the land cover maps used in the model can be observed from the transition probability matrix (2013–2015) in LCM 1 (Table 2) and the validation results, which indicate the fluctuation of land cover change in the area. For example, the probability of bare lands and woodlands being converted to developed areas was 0.6181. At the same time, developed areas also changed to other classes (0.7669). The transition probability of each land cover in LCM 2 fluctuated less than the transition in LCM 1. However, there is a probability that an error still occurred in LCM 2, as indicated in the matrix in Table 3. The images of the driver variables used in the MLP were retrieved from various sources, such as the Indonesian Geospatial Agency and WorldPop, and were developed with uncertainties embedded in every step of the process. The parameters used in the model (e.g. the combinations of drivers) also arguably affected the model accuracy (Table 4).

Discussion

This study demonstrates the value of applying both backdating and updating approaches (Linke *et al.* 2009) to mitigate data gaps found in satellite imagery for image classification. This approach was applied only to areas where land change was located, thus improving the efficiency during analysis (Toure *et al.* 2018). LCM 2 was conducted over a more extended period (2000–2015) than in LCM 1 to respond to the high fluctuations of land cover transitions within 2013–2015, including the alteration of forest types (Table 2), which resulted in a low model accuracy for LCM 1 (less than 53%). Nevertheless, an error might still occur from the different numbers of pixels in the c.2000 and c.2015 maps and the map projection process in Terrset.

Another essential factor affecting the modeling outcomes is the selection of the drivers included in the MLP process. Different sets of drivers created distinct, unique transition potential maps, which in turn generate land cover maps with different accuracies (Table 4). The model accuracy can be improved from 47.90% in LCM 1 to 81.36% in LCM 2 with all six drivers being employed. It is suggested that modeling with base maps with relatively high accuracies in LCM 1 does not automatically produce outputs with high modeling accuracy. A similar tendency was shown in the research conducted by Zubair and Ji (2015) to assess the accuracy of LCM in Kansas, USA (1992–2003). The base maps were developed using the ML and MLP classifiers, with the highest accuracy achieved when using ML on the 2003 map (93.60%). However, the model with base maps using the ML classifier had a lower accuracy (74.80%) than when using the MLP classifier (79.20%). Although this research suggests that different classifiers influence model accuracy, it also demonstrates that uncertainty occurs even when the two sets of base maps were developed using only a single classifier (ML). Thus, an analysis of the transition potential for each land cover type is a crucial step in identifying uncertainties in modeling. The importance of mitigating the uncertainties is also evident when the outcomes from land change modeling are used as input data for other models, e.g. hydrological modeling (Rani *et al.* 2019).

Conclusions

This study aims to mitigate uncertainties in the CA–Markov–MLP land change modeling of the Ci Kapundung upper water catchment area. The results show that the sources of uncertainties originate from the input data and model parameters. Modeling using highly accurate base maps from individual remote sensing data could potentially generate outputs with low accuracy. Therefore, it is necessary to reduce the differences found in maps by integrating the development process with both updating and backdating analyses. This research fills the gap in the study of mitigating uncertainty in CA–Markov–MLP modeling in those locations largely covered by forest. This research provides a framework for other similar studies for modeling land change in the upland area of a tropical region. Another issue is the limited spatial data usually found in developing countries. Only six drivers were included in the modeling, and this drawback has become the key limitation of this study. Further research could integrate a socioeconomic perspective into the analysis to include a broader perspective of drivers influencing land change, thus improving model accuracy (Overmars and Verburg 2005).

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Data and codes availability statement

The data and codes that support the findings of this study are available with the identifier(s) at https://doi.org/10.6084/m9.figshare.12277427. The SPOT 6 imagery purchased from Airbus cannot be publicly shared. Sample imagery with the same spectral combination and spatial resolution was used for the demonstration. Other datasets used in this research are included in the link and are available in the public domain of the USGS, Indonesian Geospatial Agency, and WorldPop at https://earthexplorer.usgs.gov/, http://tides.big.go.id/DEMNAS/, and https://www.worldpop.org/doi/10.5258/SOTON/WP00114, respectively.

Disclosure statement

All authors declare that they have no known competing interests.

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Eckart Lange is Professor Emeritus of Landscape at the University of Sheffield. Prior to joining the University of Sheffield in 2004, from 1990 until 2004 he was Senior Researcher in the City and Landscape Network at ETH Zürich. From 2008 to 2016 he served as a member of the scientific committee of the European Environment Agency. He held visiting appointments e.g. at the University of Tokyo and since 2017 is Visiting Professor at Tongji University, Shanghai. Eckart supervised the research and advised on the conceptualisation of the research, contributed to the methodology as well as the reviewing and editing of the manuscript.

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