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A statistical model of land use/cover change integrating logistic and linear models: An application to agricultural abandonment

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ABSTRACT

Several land use/cover change (LUCC) models have been developed to simulate future LUCC. However, current models work with the assumption that the input non-spatial variables are significant to the LUCC in hand and there is still a lack of model that could identify which non-spatial variables are significant drivers of LUCC. This paper presents a statistical model of LUCC that integrates a logistic model based on spatial drivers and a linear model based on non-spatial drivers. The logistic model produces a probability map that represents local probabilities of LUCC while the linear model produces a global probability threshold that represents a global probability of LUCC, and by comparing the two variables, LUCC is mapped. The statistical model was utilized to model agricultural abandonment in the Ifugao rice terraces, Philippines. Statistical modeling identified the significant spatial and non-spatial drivers of agricultural abandonment in the terraces. Accuracy assessment showed that simulated maps achieved accuracies suitable for LUCC simulation, demonstrating that the statistical model can be a potential tool for prediction of future LUCC.

1. Introduction

Land use/cover change (LUCC) continuously occur on the surface of the earth as a result of complex interactions between socio-economic and environmental drivers (Geist et al., 2006; He et al., 2022; Mitsuda and Ito, 2011). In the current age of globalization, LUCC typically occur as urban expansion where non-urban land use types are converted for urban use (Güneralp and Seto, 2013; Seto et al., 2011; van Vliet, 2019). Along with continuous urban expansion, globalization also drives the occurrence of other LUCC such as agricultural abandonment, deforestation, and reclamation (Cao et al., 2021; Hou et al., 2021; Wu et al., 2016; Xystrakis et al., 2017). As human society continuously interacts with the global environment to acquire its needs, hence forming perpetual socio-ecological systems (SES), it is expected that human activities will continuously cause impacts on the environment leading to recurring LUCC (Li et al., 2017; Synes et al., 2019). These LUCCs cause alterations in ecosystem services that can lead to multifaceted environmental problems (Li et al., 2016; Liu et al., 2020b; Wang et al., 2018; Zhang et al., 2019). Thus, it is imperative that future LUCC based on current trends can be projected so that planners will have the technical information to devise counter-interventions to mitigate the escalation of subjected LUCCs.

For simulating the future status of land, several LUCC models and tools have been developed in previous research (Liu and Yang, 2015; Ren et al., 2019; Verburg et al., 2019). LUCC models can be placed along a spectrum of pattern-based to process-based model types (Ren et al., 2019), On one end of the spectrum, the process-based models, which adopt “bottom-up” approach, simulate the behavior and interactions of system actors to predict the emergent spatial patterns of land cover. These models are useful for simulating scenarios based on management policies, thus they can act also as decision models. However, development of process-based models is limited by the availability of empirical resources and the ability to capture the significant system processes, hence most of the time cannot achieve high land cover prediction accuracy (Liu and Yang, 2015; Ren et al., 2019). On the other hand, pattern-based models, which adopt a “top–bottom” approach, map future land cover based on historical patterns by utilizing statistical or machine learning approaches (Boavida-Portugal et al., 2016). The advantage of such models is that future land cover maps can be simulated with relatively more available data even with lack of knowledge of

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the processes of the LUCC. Within statistical approaches, a demand-allocation approach is implemented where Markov chains compute the demand or quantitative data of LUCC while logistic models compute the allocation of the quantitative data into a map through probability maps. A limitation of this purely statistical approach is that only spatial drivers can be incorporated, but in reality, non-spatial drivers have significant effects in the quantity of LUCC. To address this limitation, hybrid models have also been developed which, like pattern-based models, adopt a demand-allocation approach but integrates process-based models to represent the demand component so that non-spatial drivers can be incorporated to project LUCC. For example, System Dynamics has been used in several studies to represent how aggregated system structures affect the quantity of LUCC (Dang and Kawasaki, 2017; Mao et al., 2014; Xu et al., 2016). Previous studies have also incorporated Agent-based models (ABM) to incorporate the decision making in an SES (Liu et al., 2020a; Mustafa et al., 2017; Tang and Yang, 2020).

Although there already exist hybrid models that can incorporate non-spatial drivers to project future LUCC, two limitations can be found in the usage of these models. First, as much as current hybrid models can accept various non-spatial variables as inputs, it is possible that the variables being used by a specific model may not be significant drivers of an LUCC being studied. For example, agricultural abandonment is a multifaceted global phenomenon that is driven by various drivers depending on the social, economic, and environmental settings of a landscape (Gellrich and Zimmermann, 2007; Osawa et al., 2016; Pazúr et al., 2020). It is thus necessary that in projecting the future agricultural abandonment in a study area, the significant spatial and non-spatial drivers be first identified so that they can all be incorporated in a simulation model. Second, development of a model that incorporate all the significant drivers of an LUCC model requires capturing the complexity of the interactions and feedbacks of all these drivers in a socio-ecological system (Liu and Yang, 2015; Ren et al., 2019). However, modeling of these systems requires the participation of experts and stakeholders which possess the empirical knowledge regarding the SES in hand and a skilled modeler that can devise a model structure to incorporate this empirical knowledge. For planning purposes, the participation of such knowledgeable and skilled personnel is mostly not feasible. For simple prediction purposes such as projecting LUCC brought by changes in some driving factors, a more general statistical model which can also incorporate non-spatial drivers can be useful. Looking into the spectrum of process-based to pattern-based models of LUCC, there has not been a previously developed statistical pattern-based model that can incorporate non-spatial drivers.

In order to propose a method of identifying both the significant spatial and non-spatial drivers of LUCC and simplifying the projection of future LUCC, this study presents a statistical model of LUCC which integrates both a logistic model based on spatial explanatory variables and a linear model based on non-spatial explanatory variables. Specifically, the proposed statistical model simulates LUCC by mapping a probability map and a global probability threshold through the logistic model and linear model, respectively. By comparing each pixel in the probability map with the global probability threshold, the true-or-false occurrence value of LUCC in every pixel is mapped. To test the statistical model's capability in simulating LUCC maps, the model was applied in simulating the agricultural abandonment in the Ifugao rice terraces in the Philippines, where a UNESCO World Heritage site is situated. The accuracies of the simulated maps were assessed by comparing the simulated maps with actual maps of agricultural abandonment using accuracy measures of Fuzzy Kappa and Absolute Deviation Percentages (ADP).

2. Model description

In pattern-based and hybrid models of LUCC, a logistic model is used to act as an allocation component which produces a probability map (also called suitability map) of occurrence of an LUCC (Gellrich et al., 2007; Hu and Lo, 2007). A logistic model is expressed as a function of the form

$$P(u,v,t)=\frac{1}{1+e^{-\left(a_0+\sum_{i=1}^{m}a_ix_i(u,v,t)\right)}}=\frac{1}{1+e^{-(a_0+a_1x_1+a_2x_2+\cdots+a_mx_m)}} \tag{1}$$

where P is the probability of the LUCC to occur at a pixel of indices (u, v) at a time period t and has a range from 0 to 1 where a higher value indicates a higher likelihood of LUCC occurrence, $x_i(i=1,2,\cdots,m)$ is a spatial explanatory variable that varies through space and time, and $a_i(i=0,1,\cdots,m)$ is a parameter estimated from logistic regression, where a_0 is the intercept and a_1, a_2, …, a_m are the respective coefficients of the spatial explanatory variables x_1, x_2, …, x_m (Cheng and Masser, 2003; Shu et al., 2020). Logistic regression, which estimates the parameters of the logistic model, is implemented by denoting a binary variable Z as a dependent variable, where Z takes only values of 1 or 0, a value of 1 denoting the LUCC occurred while 0 denoting the LUCC did not occur. However, as the logistic model only produces values of probability that ranges from 0 to 1, the logistic model in the form of Equation (1) does not produce the spatial pattern of occurrences of LUCC but instead produces just the spatial pattern of probability. Hence, for the simulation of future LUCC, a demand module is incorporated which produces quantitative data based on non-spatial explanatory variables (Liu and Yang, 2015; Ren et al., 2019). Different types of demand modules have been utilized such as System dynamics (Dang and Kawasaki, 2017; Mao et al., 2014; Xu et al., 2016), and Agent-based Modeling (Tang and Yang, 2020).

A workaround from computing a quantitative data of LUCC is to implement thresholding of probability values in a probability map. Thresholding is implemented by assigning a global probability threshold $P_{threshold}$ and using the following equation to compute for the LUCC occurrence Z:

$$Z(u,v,t)=\begin{cases}1, P(u,v,t)\rangle P_{threshold}(t)\\ 0, P(u,v,t)\leq P_{threshold}(t)\end{cases} \tag{2}$$

Equation (2) indicates that the occurrence of LUCC in a pixel is based on the comparison of the pixel's probability value with a global $P_{threshold}$ at period t with the probability value in a pixel, where the lower is the $P_{threshold}$, the higher is the chance that the LUCC will occur in the pixel. Thus the $P_{threshold}$ acts as a global model parameter that increases or decreases the likelihood of LUCC in a map, hereby affecting the quantitative value of LUCC in an inversely proportional manner. This also implies that different probability threshold values will produce different simulated maps which will have different accuracies when compared to actual maps of LUCC. Hence, an optimal probability threshold exists where the difference between simulated and actual maps will be at a minimum and accuracy will be maximized. Previous studies implemented different strategies to find the optimal thresholding values such as through parametric methods (Sandnes, 2011) or by optimizing an objective function (Li et al., 2020). In the study, an optimal probability threshold value was determined by implementing an optimization routine with the objective to find the $P_{threshold}$ that maximizes the similarity statistic between simulated and actual LUCC maps.

The probability of LUCC, P, was related to spatial explanatory variables because it is spatial in nature. On the other, the $P_{threshold}$ is a global variable that is constant throughout a study area, thus it is a non-spatial in nature and can be related to non-spatial explanatory variables. To relate the global probability threshold to non-spatial explanatory variables, a linear model is utilized in the form

$$P_{threshold}(t)=b_0+\sum_{j=1}^{n}b_jy_i(t)=b_0+b_1y_1+b_2y_2+\cdots+b_ny_n \tag{3}$$

where $P_{threshold}$ is the global probability threshold value for converting a probability map at time period t into an LUCC map, $y_i(j=1,2,\cdots,n)$ is a non-spatial explanatory variable that varies through time, and $b_i(j=0,1,\cdots,n)$ is a parameter estimated from linear regression, where b_0 is the intercept and $b_1, b_2, \ldots, b_n$ are the respective coefficients of the non-spatial explanatory variables $y, y_2, \ldots, y_n$. To produce the linear model in Equation (3), linear regression is implemented where the dependent variable is $P_{threshold}$ values through time and the explanatory variables are non-spatial drivers, variables that are constant through the mapping area but varies through time. Based on accuracy statistics of the linear regression, variables that are found significant for explaining the variation in quantities of LUCC through different periods will be added to the linear model.

Based on equations (1), (2), and (3), this study developed a statistical model which incorporates a logistic model and a linear model for simulating LUCC at pixel (u, v) at time period t with the form:

$$Z(u,v,t) = \begin{cases} 1, \dfrac{1}{1 + e^{-\left(a_0 + \sum_{i=1}^{m} a_i x_i(u,v,t)\right)}} > b_0 + \sum_{j=1}^{n} b_j y_j(t) \\ 0, \dfrac{1}{1 + e^{-\left(a_0 + \sum_{i=1}^{m} a_i x_i(u,v,t)\right)}} \leq b_0 + \sum_{j=1}^{n} b_j y_j(t) \end{cases} \quad (4)$$

The left side of Equation (4), which comes from the logistic model, dictates the local probabilities of LUCC by producing a probability map based on spatial drivers (Fig. 1). The right side of the equation, which comes from the linear model, dictates the global probability of LUCC by computing for a global probability threshold based on non-spatial drivers. By comparing every pixel in the probability map with the global probability threshold, an LUCC map will be produced.

3. Study area

The proposed statistical model for LUCC was applied for modeling agricultural abandonment in a watershed containing the Bangaan terrace cluster, one of the United Nations Educational, Scientific, and Cultural Organization (UNESCO) world heritage site in the Ifugao rice terraces, Philippines (Fig. 2). The rice terraces in the watershed have been experiencing continuing permanent agricultural abandonment since the 1990 s due to various driving factors (Estacio et al., 2022). Farmers cite erosion of their agricultural lands as one of the reasons for

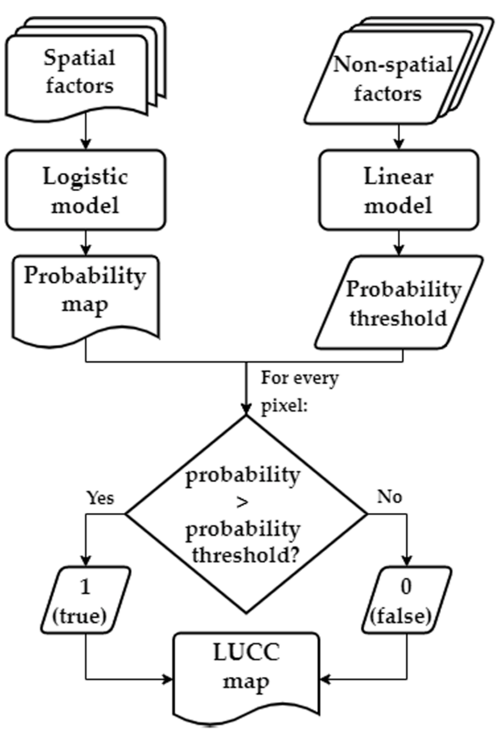

Fig. 1. The conceptual framework of the statistical model for simulating maps of LUCC based on spatial and non-spatial factors.

abandoning their lands (Calderon et al., 2009). Water availability is also cited as a cause for abandonment, where water supply from streams are insufficient during the dry season (Calderon et al., 2009). Climate changes were also observed through the past decades such as changes in temperature and precipitation, which qualitatively aligned with farmer observation (Soriano et al., 2017). Because of several socio-economic and environmental factors that can be attributed to the agricultural abandonment in the Ifugao rice terraces, it is of importance to analyze the impact of each of these factors to the ongoing agricultural abandonment and to predict future changes based on past trends by developing a statistical model.

4. Methods

The methodological workflow was implemented in five main steps (Fig. 3). First, GIS techniques were utilized to prepare spatial and non-spatial data. Second, logistic regression was implemented based on point samples of the binary response variable and spatial explanatory variables to produce a logistic model. Third, optimization based on a Genetic Algorithm (GA) was implemented to find the optimal global probability threshold for every probability map produced by the logistic model. Fourth, linear regression was implemented based on values of the optimal global probability threshold response variable and non-spatial explanatory variables to produce a linear model. Lastly, the accuracies of the simulated maps were assessed by comparing it to the actual maps of agricultural abandonment.

4.1. Data preparation

Four types of data were prepared for the statistical modeling of agricultural abandonment: Raster files of LUCC binary response variable, vector files of sample points, raster files of spatial explanatory variables, and tables values of non-spatial explanatory variables. A more detailed description of the preparation of these data can be found in the supplementary material.

To prepare binary maps of continuously cultivated and permanently abandoned paddy fields, time-series land cover maps from 1990 to 2015 in five-year intervals were processed using Geographic Information System (GIS) (Fig. 4). Samples of the binary response variable were acquired by creating sample points that do not exhibit spatial autocorrelation. All sets of created sample points exhibited a maximum magnitude of Moran's I of 0.027, hence the points can be considered random (Cheng and Masser, 2003; Xiao et al., 2015). Raster files of spatial explanatory variables were then prepared based on previous studies on the abandonment of mountainous agricultural landscapes (Nainggolan et al., 2012; Pazúr et al., 2020; Xystrakis et al., 2017) and also subjected to data availability (Fig. 5). The values of all spatial explanatory variables were extracted into the created sample points so that each point has a binary value of agricultural abandonment occurrence alongside values of the spatial explanatory variables. Lastly, non-spatial drivers such as economic, social, and environment variables were selected and prepared based on previous studies on mountainous agricultural landscapes (Table 1) (Liu et al., 2020a; Mao et al., 2014; Xu et al., 2016).

4.2. Logistic regression of LUCC binary response variable with spatial explanatory variables

To identify the significant spatial drivers of agricultural abandonment, logistic regression was implemented using the 1500 samples points of binary response variable and spatial explanatory variables gathered from 1990 to 2015. The accuracy of the resulting logistic model was assessed using Pseudo R-square and ROC (Relative Operating Characteristic) values. If the Pseudo R-Square is greater than 0.2, the produced logistic model for the respective period was deemed to be of good fit to be used to explain the significance of each spatial driver to the

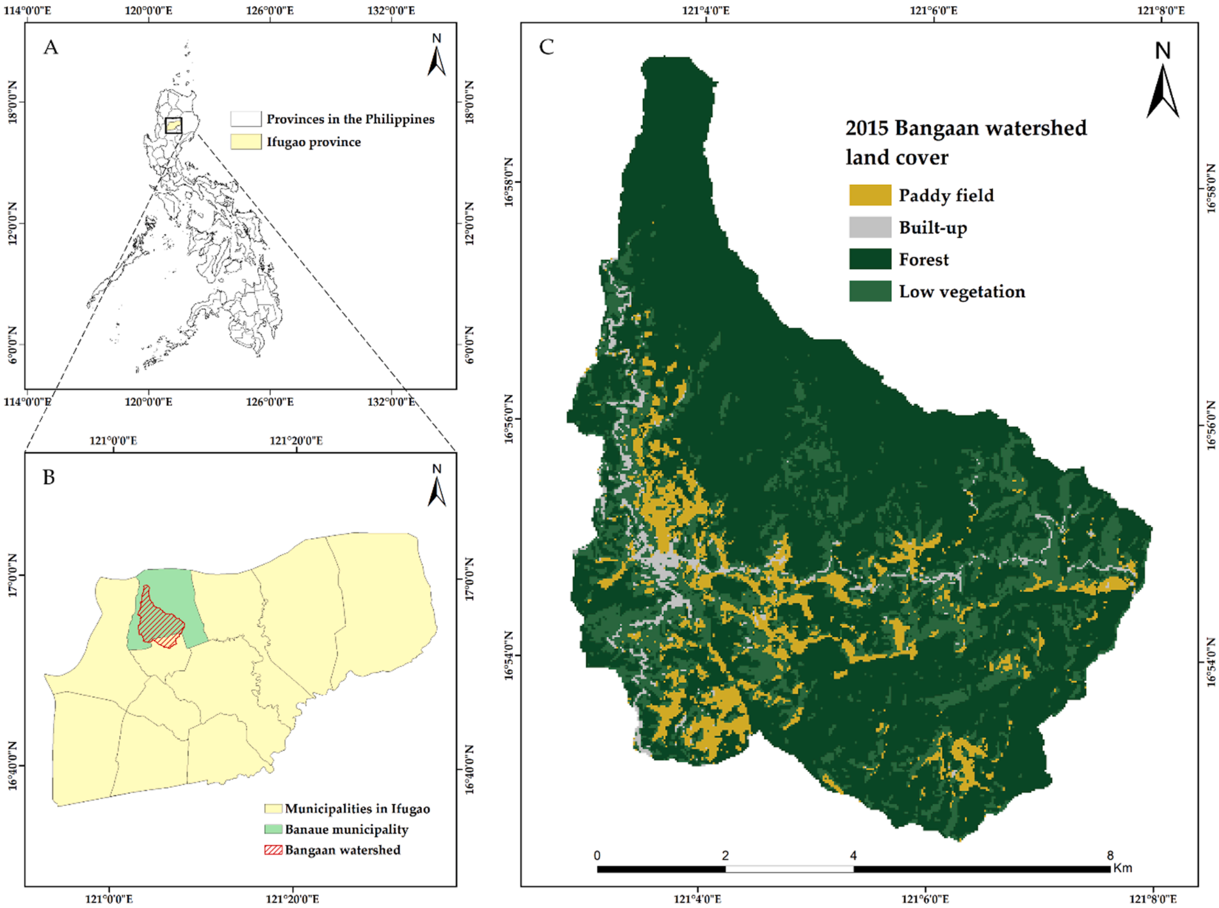

Fig. 2. The location of the study area, Bangaan watershed: (A) The location of Ifugao province in the Philippines; (B) The location of the Bangaan watershed and Banaue municipality in the Ifugao province; (C) The land cover in the Bangaan watershed in the year 2015.

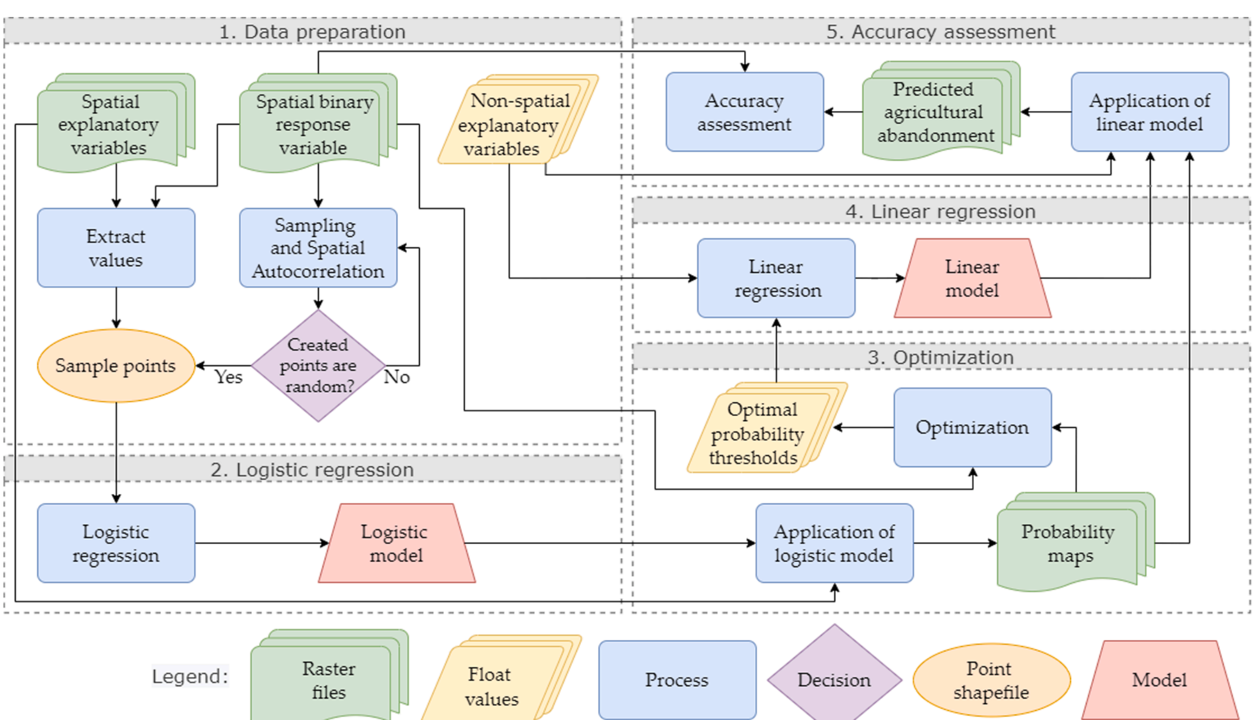

Fig. 3. Workflow of the modeling process in five main steps.

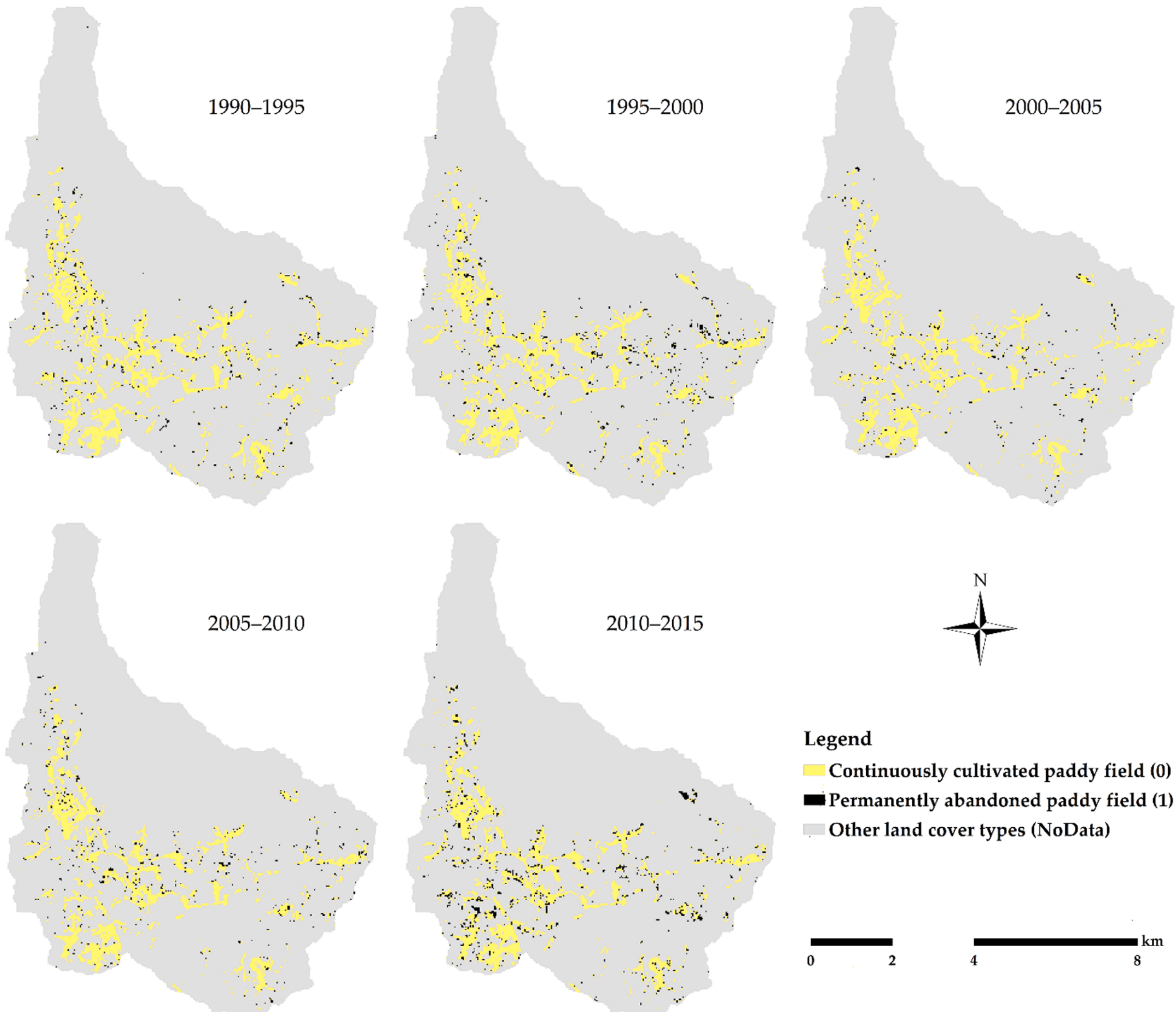

Fig. 4. Spatial distribution of the continuously cultivated and permanently abandoned paddy fields through five-year periods from 1990 to 2015.

occurrence of agricultural abandonment (Hu and Lo, 2007). Logistic regression was implemented using R 3.3.0.

4.3. Derivation of optimal probability threshold by optimization

The next step is to derive the optimal probability thresholds for the probability maps of every period. First, probability maps for every period were generated using the produced logistic model, utilizing the spatial explanatory variables for every period. Optimization was then implemented using a Genetic Algorithm (GA) to find the probability threshold that will yield the highest Fuzzy Kappa statistic between a simulated map and an actual map. Fuzzy Kappa is a statistic for comparing the similarities between two maps based on local neighborhood, and is closer to how human observers compare maps (Drogoul et al., 2016; Visser and De Nijs, 2006). Hence, optimizing the probability threshold based on maximizing the fuzzy kappa statistic is akin to finding a simulated map with the least difference between an actual map. It should be noted that Fuzzy simulation, another accuracy statistic, was not used because an end-state land use/cover map is used as input in this statistic, and a map simulated in this step is an LUCC (land use/cover change). A Genetic Algorithm, which is a population-based search algorithm that aims to find the best solution, was set with the following parameters: population = 7, generations = 5, crossover = 0.7, mutation = 0.1 (Katoch et al., 2021; Mirjalili, 2019). After implementing the GA, optimal probability thresholds for each period were obtained. Coding of the GA was implemented in the GAMA platform (Taillandier et al., 2019).

4.4. Linear regression of optimal probability thresholds with non-spatial explanatory variables

To relate the variation of the global probability thresholds with non-spatial explanatory variables, multivariate linear regression was implemented to create a linear model. First, as several non-spatial explanatory variables were prepared, different combinations of variables were tested for the linear regression. For every combination, the P-value of every non-spatial explanatory variable was checked for its significance (if $P < 0.05$). The significance F of the model was also checked for is significance (if $F < 0.05$), which indicates that the linear model fits the data better than a model with no explanatory variables. Once all the P-values and significance F in a combination of variables are significant, the adjusted R-squared of the model was recorded. After testing different combinations of variables, the combination with the recorded highest adjusted R-squared was chosen as the non-spatial explanatory variables of the linear model of global probability threshold. Linear regression was implemented using the Data Analysis tools in Microsoft Excel.

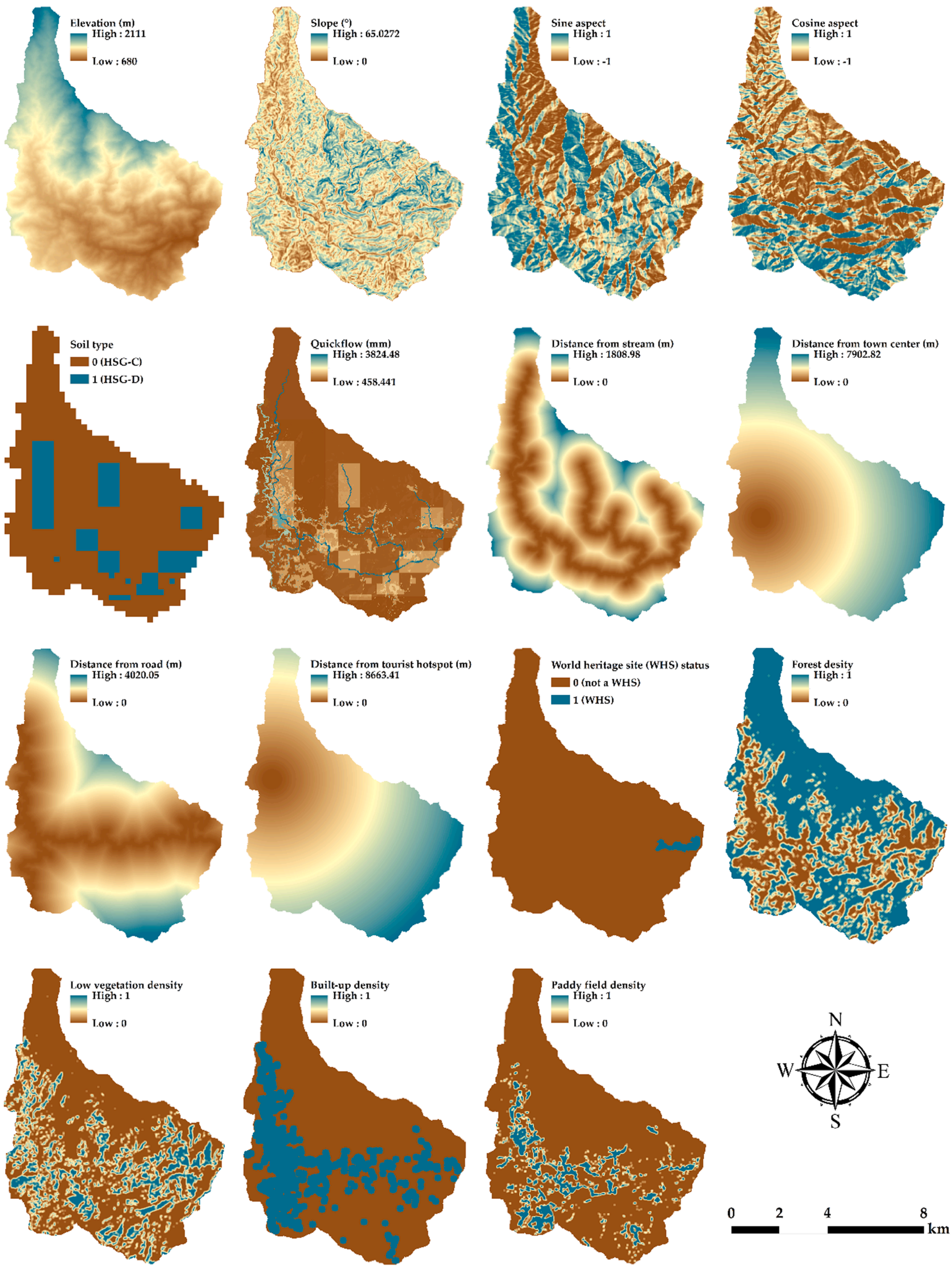

Fig. 5. Raster layers of spatial explanatory variables included in the logistic regression (sample layers for the year 2000).

Table 1
List of non-spatial explanatory variables included in the linear regression to model global probability thresholds of permanent agricultural abandonment.

Category	Variable (unit)
Land cover	Paddy field total area (m^2) Low vegetation total area (m^2) Forest total area (m^2) Built-up total area (m^2)
Demography	Average household size Number of households Household Population
Climate	Precipitation – annual mean (mm) Precipitation – 5-year smooth (mm) Mean Temperature – annual mean (°C) Mean Temperature – 5-year smooth (°C) Min Temperature – annual mean (°C) Min Temperature – 5-year smooth (°C) Max Temperature – annual mean (°C) Max Temperature – 5-year smooth (°C)

4.5. Accuracy assessment of modeled maps

Using the produced linear model where non-spatial explanatory variables and probability maps were used as inputs, binary maps of agricultural abandonment for every period were simulated. To assess the accuracy of the simulated agricultural abandonment maps and the reliability of the statistical model, the simulated maps were compared with its respective actual maps by computing for the Fuzzy Kappa and Absolute Deviation Percentages (ADP) statistics. Unlike Fuzzy Kappa statistic which computes similarities based on local neighborhood, ADP is a global indicator that computes the differences between maps based on the quantity of each land cover class (Truong et al., 2016). Using the two statistics, along with visual comparison of the actual and simulated maps, the accuracy of the model was assessed if it can be used for LUCC simulation.

5. Results

5.1. Logistic regression of agricultural abandonment with spatial explanatory variables

Logistic regression based on 1500 samples from 1990 to 2015 produced a logistic model with Pseudo-R squared value of 0.225 and AUC ROC of 0.804 (Table 2), indicating that the model was of good-fit and can be used for explaining the significant drivers of agricultural abandonment in the rice terraces. Slope and paddy field density were the most significant drivers of agricultural abandonment in the logistic model ($P < 0.001$), where areas with higher slope values and low density of neighboring paddy fields have the highest chances of abandonment. The next set of significant variables were cosine aspect, quickflow, and low vegetation density ($P < 0.01$), which indicates that the direction of the field, quickflow during rainy periods, and neighborhood percentages of low vegetation also contribute to the likelihood of abandonment. Other significant drivers were distance to town center, distance to road, world heritage site status, and forest density ($P < 0.05$).

5.2. Linear regression of optimal probability threshold with non-spatial explanatory variables

Optimal probability thresholds for maximizing the similarity between simulated maps and actual maps were derived using a GA (Table 3). The minimum attained Fuzzy Kappa statistic for all simulated maps was 0.3718 while the maximum statistic is 0.5062. On the other hand, the optimal probability threshold ranges only from 0.73 to 0.86, revealing that the optimal probability threshold only underwent small variations between periods. This however does not imply that the subsequent quantitative change in LUCC will have the same variation as quantitative change also depends in the values in the probability maps.

Using the optimal probability thresholds as the response variable, linear regression based on using forest total area, precipitation (5-year smooth), and maximum temperature (annual mean) as non-spatial explanatory variables produced a linear model with adjusted R-squared of 0.9999996 and significance F of 0.0003817, indicating that the linear model was of excellent fit (Table 4). All explanatory variables attained significant P values ($P < 0.01$), with forest total area and max temperature having P values<0.001.

5.3. Statistical model for mapping agricultural abandonment

By integrating the logistic model based on spatial explanatory variable and the linear model based on non-spatial explanatory variables, a statistical model was derived for mapping agricultural abandonment, in the form:

Table 2
Summary statistics of the logistic model of local probabilities of agricultural abandonment.

Spatial variable (unit)	Coefficients	Standard error	Z	P-value
(Intercept)	ns	ns	0.338	0.653
Elevation (m)	ns	ns	−0.807	0.420
Slope (°)	0.0499***	0.00851	5.868	0.000
Sine aspect	Ns	ns	1.682	0.092
Cosine aspect	−0.303**	0.0939	−3.221	0.001
Soil type	ns	ns	0.432	0.666
Quickflow (mm)	0.000360**	0.000111	3.243	0.001
Distance to stream (m)	ns	ns	0.950	0.342
Distance to town center (m)	0.000198*	0.0000836	2.366	0.018
Distance to road (m)	−0.000281*	0.000129	−2.179	0.029
Distance to tourist hotspot (m)	ns	ns	−0.532	0.594
World heritage site status	−0.841*	0.404	−2.080	0.038
Forest density	1.210*	0.587	2.057	0.040
Low vegetation density	2.010**	0.617	3.256	0.001
Built-up density	ns	ns	−1.456	0.145
Paddy field density	−2.540***	0.544	−4.673	0.000
Accuracy: Pseudo R-squared	0.225			
Accuracy: AUC ROC	0.804			

ns: P greater than 0.05 (insignificant).
* : $0.01 \le P < 0.05$.
** : $0.001 \le P < 0.01$.
*** : $P < 0.001$.

$$Z = \begin{cases} 1, \dfrac{1}{1+e^{-1\begin{pmatrix} 0.050S - 0.303C \\ +3.60(10^{-4})Q \\ +1.98(10^{-4})T \\ -2.81(10^{-4})R \\ -0.841H + 1.21D_L \\ +2.01D_F - 2.54D_P \end{pmatrix}}} > 7.39 - 3.94(10^{-4})A_F - 3.55(10^{-5})P_A - 0.170T_{max} \\ 0, \dfrac{1}{1+e^{-1\begin{pmatrix} 0.050S - 0.303C \\ +3.60(10^{-4})Q \\ +1.98(10^{-4})T \\ -2.81(10^{-4})R \\ -0.841H + 1.21D_L \\ +2.01D_F - 2.54D_P \end{pmatrix}}} \leq 7.39 - 3.94(10^{-4})A_F - 3.55(10^{-5})P_A - 0.170T_{max} \end{cases} \quad (5)$$

where Z is the occurrence of agricultural abandonment in a pixel in a particular period where a value of 1 denotes occurrence while 0 denotes no occurrence, S is the slope, C is the cosine aspect, Q is the Quickflow, T is the distance to town center, R is the distance to road, H is the status as world heritage site, D_L is the low vegetation density, D_F is the forest density, D_P is the paddy field density, A_F is the forest total area, P_A is the average precipitation within 5 years, and T_{max} is the annual mean of the daily maximum temperature. The statistical model includes nine spatial explanatory variables and three non-spatial explanatory variables. All variables vary through time, hence given a pixel of indices (u, v), the occurrence of agricultural abandonment at different periods may vary depending on the temporal variation of the explanatory variables (such as quickflow, forest density, or precipitation).

Table 3
Optimal probability thresholds for maximizing the Fuzzy Kappa statistic between simulated and actual maps of agricultural abandonment.

Period	Optimal probability threshold	Maximum fuzzy kappa
1990–1995	0.82	0.3718
1995–2000	0.86	0.5062
2000–2005	0.87	0.3978
2005–2010	0.87	0.4440
2010–2015	0.73	0.4327

Table 4
Summary statistics of the linear model of global probability threshold of agricultural abandonment.

Temporal non-spatial variables (unit)	Coefficients	Standard error	t-stat	P-value
(Intercept)	7.3859***	0.00342	2158.31	0.00029
Forest total area (m^2)	−0.00039391***	0.000000208	−1895.66	0.00034
Precipitation – 5-year smooth (mm)	−0.0000354805**	0.0000000940	−377.446	0.0017
Max Temperature – annual mean (°C)	−0.16666***	0.000117	−1422.39	0.00045
Accuracy: Adjusted R-squared	0.9999996			
Accuracy: Standard error	0.0000357			
Accuracy: Significance F	0.0003817			

5.4. Accuracy assessment of modeled maps

Through the statistical model, maps of agricultural abandonment for every period were simulated using the spatial and non-spatial explanatory variables in every respective period (Fig. 6). The accuracies of these simulated maps were assessed by comparing them to the actual maps of agricultural abandonment for the respective period (Table 5). As the fit of the linear model is almost equal to 1.0 (Table 4), the derived Fuzzy Kappa statistics for the simulated maps are almost equal as those derived from the optimal probability thresholds (Table 3). The maximum ADP for all modeled maps was 1.053%, indicating that the differences in derived quantitative values of agricultural abandonment is minimal, even when optimization of probability threshold is aimed on maximizing Fuzzy Kappa which focuses on neighborhood similarities.

6. Discussion

6.1. Implications of the developed LUCC statistical model

The structure of the developed statistical model of LUCC that is composed of a logistic model and a linear model implies a different mechanism of simulating LUCC than the demand-allocation models that also incorporate a logistic model. Demand-allocation models incorporate two modules, allocation and demand (Liu and Yang, 2015; Ren et al., 2019). The demand module generates the quantitative value of LUCC by adopting models such as System dynamics or Markov Chain (Boavida-Portugal et al., 2016; Dang and Kawasaki, 2017; Xu et al., 2016). The derived quantitative value of land cover change from the demand module are then allocated into an LUCC map through the allocation module. Thus, the allocation module dictates the spatial pattern of LUCC by deriving probability maps using a logistic model derived from historical patterns of spatial explanatory variables. Through a probability map, LUCC is allocated to pixels starting from the pixel with the highest probability of change going to the next highest

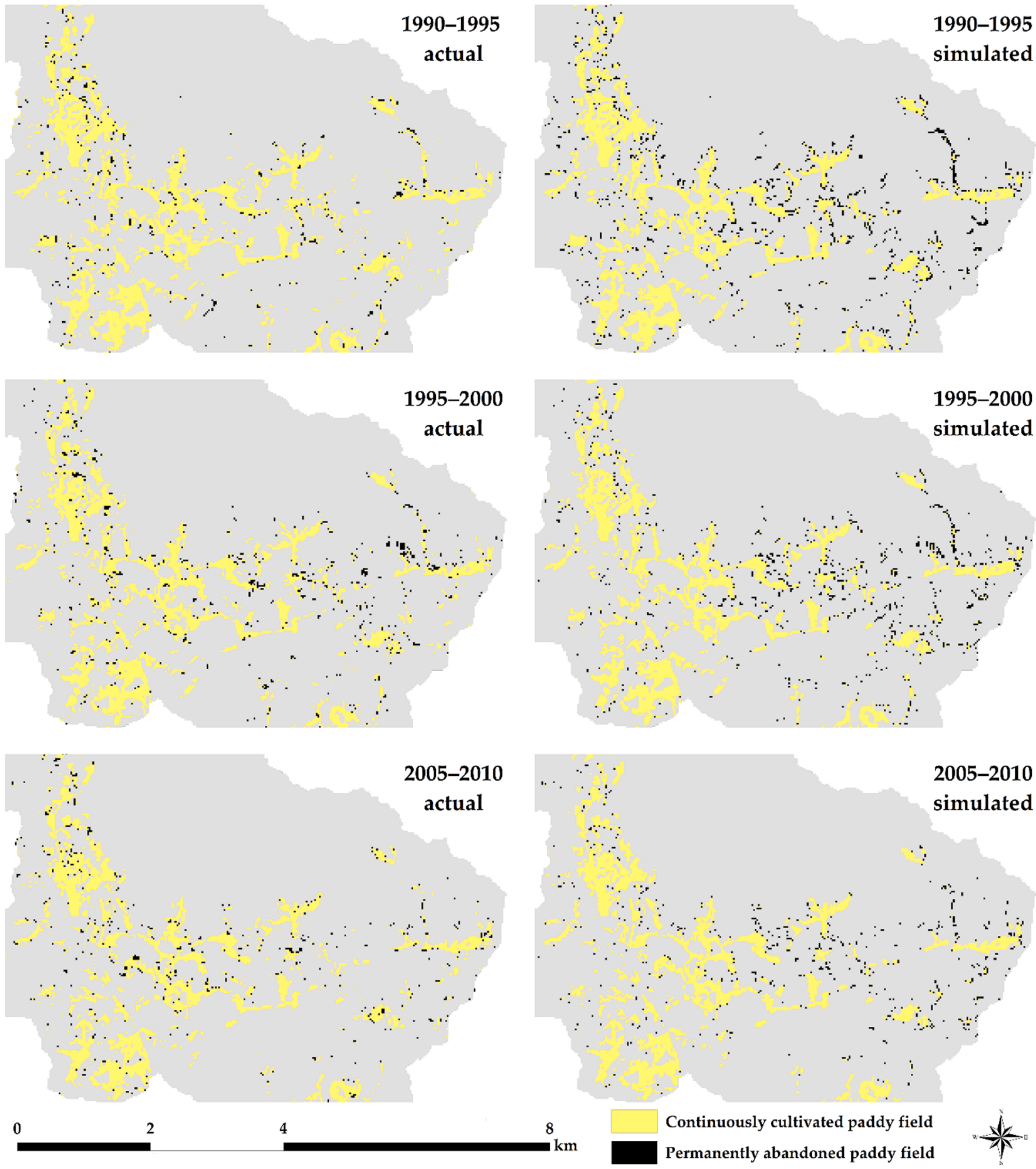

Fig. 6. Side-by-side comparison of actual and simulated agricultural abandonment maps for the periods 1990–1995 (the period with the worst Fuzzy Kappa and ADP), 1995–2000 (the period with the best Fuzzy Kappa), 2010–2015 (the period with the best ADP).

Table 5
Accuracy statistics for the simulated agricultural abandonment maps of every period.

Period	Fuzzy Kappa	ADP
1990–1995	0.3718	1.053%
1995–2000	0.5062	0.277%
2000–2005	0.3978	0.576%
2005–2010	0.4440	0.113%
2010–2015	0.4327	0.863%

one, until the quantitative value of LUCC is met. Previous studies have also incorporated rules in allocation such as cellular automata that takes into account neighborhood effects and limitations on transitions (Mao et al., 2014; Mustafa et al., 2017).

In the proposed statistical model, instead of a demand module, the model utilizes a linear model of global probability threshold which dictates which pixels undergo LUCC based on comparing the local probability and the global probability threshold. This structure implies that the probability map also dictates the quantitative value of the LUCC, as compared to demand-allocation models where probability maps only dictate the spatial pattern. For example, in a demand-allocation model, adding a constant probability value in a particular area in the probability map will not affect the total quantitative value of the LUCC but will only affect the spatial pattern. However, in the developed statistical model, subtracting a constant probability value in a particular area will not only affect the spatial pattern but also the quantitative value. In relation to this, global probability thresholds hold a role of dictating on which probability value pixels start to change, where lower thresholds lead to more changes, and vice versa. Global probability thresholds can hence be treated as an inverse global probability of the LUCC occurring in the whole mapping area.

In essence, spatial explanatory variables, which dictate the probability maps, control the local probabilities of LUCC and hold an effect not only to the spatial pattern but also to the quantitative value of LUCC. For example, in the case study, adding more conservation areas in a political restriction variable will affect the simulated quantitative value of agricultural abandonment. Another example is improving the values in a productivity variable which will lead to less quantities of agricultural abandonment. In a demand-allocation model which uses system dynamics, modifying the stocks or flows in the SD module should be implemented if quantitative value of LUCC based on changes in spatial variables need to be simulated. However, in the developed model, this is not needed as changes in the spatial explanatory variable directly affect the quantitative value of LUCC.

On the other hand, non-spatial explanatory variables, which dictate the global probability threshold, control the global probability of LUCC which affects the quantitative value of LUCC. For example, the results show that precipitation has a significant inverse linear relationship with the global probability threshold. As the global probability threshold has a negative relationship with quantitative value of LUCC, precipitation can be treated as a determinant that has a positive relationship on the probability of agricultural abandonment, where an increase in precipitation leads to an increase in the overall probability of agricultural abandonment in the study area.

Lastly, the developed statistical model simulates LUCC by utilizing the generated significant statistical relationships with spatial and non-spatial explanatory variables. In modeling terms, the statistical model acts like a black box that accepts inputs and generates an output without an understanding of the socio-ecological processes that produce the statistical relationships between entities. This differentiates itself from process-based models where a thorough manifestation of system processes is used to generate outputs based on inputs. Thus, in the spectrum of LUCC models, the developed statistical model can be put under the classification of pattern-based models (Ren et al., 2019). Regardless of the model type, the developed statistical model also follows the capabilities of other models in simulating future scenarios where inputs or parameters are modified to match the circumstances of a scenario. For example, as the statistical model has shown that "distance to road" is a significant spatial driver of agricultural abandonment, modifying the map of this variable to show a scenario where new roads are established can be implemented to simulate the effects of building roads to agricultural abandonment.

6.2. Application of the model: Spatial and non-spatial drivers of agricultural abandonment

The produced logistic model for the period from 1990 to 2015 attained a Pseudo R-squared a value greater than 0.2, indicating that models is of good fit and can be used to explain the explain the significance of each spatial driver to the occurrence of permanent abandonment in each period (Hu and Lo, 2007). Based on the logistic model, slope and paddy field density were the most significant spatial drivers of agricultural abandonment in the rice terraces. This indicates that fields of steep slopes and low neighborhood percentages of paddy field experienced the highest probability of agricultural abandonment. This result aligns with the study of Corbelle-Rico et al. (2012) which found that agricultural parcels with steeper slopes and higher distances to farm (hence, less neighborhood of agricultural parcels) lead to more abandonment. The next set of significant variables were cosine aspect, quickflow, and low vegetation density. Results show that fields that face south, experience heavy quickflow during rainy periods, and have high neighborhood percentages of low vegetation are also most likely to experience permanent abandonment. Results for the low vegetation density aligned with the study of Pazúr et al. (2014) which showed that fields that are nearer to shrubs have higher chances of being abandoned. The last set of significant spatial drivers are distance to town center, distance to roads, status as world heritage site, and forest. Fields that are far from the town center, are near to roads, are not part of the world heritage site, and have high neighborhood percentages of forest also have high chances of being abandoned. Pazúr et al. (2020) also showed that forest density increases the likelihood of abandonment. Results for the distance to town center aligned with the results of previous studies, such as of Pazúr et al. (2014) which showed that increasing the distance to a county center increased the likelihood of agricultural abandonment and of Perpiña Castillo et al. (2021) which showed that remoteness, represented by the travelling time to the nearest town, also increased the likelihood of agricultural abandonment. For the results of the world heritage site, it is worth noting that status as world heritage site was highly significant ($P < 0.01$) for the particular period of 2000–2005, which may be attributed to the inclusion of the Ifugao rice terraces heritage cluster into UNESCO's list of World Heritage in Danger in 2001 (UNESCO, n.d.), influencing the farmers to exclude the fields in the heritage cluster for abandonment. Increase in probability of abandonment in areas neared to roads may be attributed to the conversion of paddy fields near roads to built-up cover, which is related to the findings of Nainggolan et al. (2012) which showed that likelihood of abandonment was higher in areas close to the village due to the demand for settlement expansion.

For the linear model, the linear regression attained a significance F of 0.0003817, indicating that the non-spatial explanatory variables were of good fit to the global probability threshold. The linear model revealed that total forest area, precipitation, and average daily maximum temperature were significant determinants of the probability of agricultural abandonment. Higher areas of forest cover led to higher probability of agricultural abandonment in the study area. This is in line with previous studies in the Ifugao rice terraces where increases in forest cover decreased the total water yield, thereby promoting further agricultural abandonment (Estacio et al., 2022; Soriano and Herath, 2018). This implies that even though water scarcity is an existing problem in the Ifugao rice terraces, high precipitation promotes agricultural abandonment because of the resulting increase in erosion. Combining the implications of the total forest area and precipitation, results indicate that it is the water yield during the dry season, not the amount of precipitation during the wet season, that is important in the rice terraces as cultivation of rice occurs during the dry season. Lastly, increasing daily maximum temperature was found to increase chances of abandonment. This can also be related to the water yield as the rice terraces suffer insufficient supply of water in the dry season, hence the paddy fields are sensitive to increases in evaporation brought by increasing temperature, leading to more abandonment.

6.3. Future direction in LUCC modeling

Simulated maps of agricultural abandonment using the statistical model attained Fuzzy Kappa statistics ranging from 0.3718 and 0.5062 and ADP ranging from 1.053% to 0.277%, which are satisfactory accuracy values for LUCC simulations. For example, the hybrid ABM developed by Mustafa et al. (2017) simulated maps in three experiments and achieved Fuzzy Kappa ranging from 0.3942 to 0.4792 and ADP ranging from 43.22% to 22.11%. The simulated maps from the developed statistical model achieved fuzzy kappa values in the same range while the ADP values are much more accurate. Ahmed et al. (2013) compared maps simulated from three types of Markov models (Stochastic, Cellular Automata, and Multi-layer Perceptron) and calculated Fuzzy Kappa accuracies of 0.304, 0.862, and 0.953, respectively. Based on this, the performance of the statistical model can be assessed to be in between a Stochastic Markov model and a Cellular Automata Markov model. Based on this assessment, the statistical model can then be deemed suitable for simulating future LUCC maps.

The statistical model differentiates itself from other LUCC models through its capability of identifying the significant non-spatial drivers of an LUCC. In using established LUCC simulation models, input variables are already set thus users are limited with their ability to incorporate variables that may be significant for the LUCC. A user can opt to develop a hybrid LUCC model coupled with system dynamics or agent-based model to be able to incorporate all significant non-spatial drivers. However, building such a complicated model needs detailed capturing of the system processes hence can take a lot of time. Thorough calibration of the model to ensure that generated LUCC maps are of acceptable accuracy also takes plenty of trial-and-error. With the proposed statistical model, the significant non-spatial drivers can be identified and, at the same time, be incorporated in the model right away for simulation.

To simulate future LUCC through the statistical model, generating the future values of the explanatory variables is essential, thus coupling with another established models to derive these future values may be essential if the situation calls for it. For example, in the case study where future agricultural abandonment is to be simulated, predictions of some explanatory variables are needed such as future land cover maps, quickflow maps, precipitation, and temperature. For this purpose, existing models can be utilized such as Markov Chain for predicting future land cover values, the InVEST seasonal water yield model for mapping quickflow, and climate models for projecting future trends of precipitation and temperature.

Aside from being used for simulation of scenarios, the statistical model can also be used as a step before using process-based models to identify first the significant drivers of LUCC. After the identification of the significant drivers of LUCC using the statistical model, a user will then be informed on which current process-based LUCC model is most suitable to use for scenario simulation. At the same time, a modeler can also use the model to gain insight on the drivers of a LUCC before proceeding to model the socio-ecological processes of an LUCC in hand.

A main limitation of the statistical model that users should remember is its capability of simulating only one type of LUCC, as in the case study, agricultural abandonment. In reality, LUCC occurs in various land cover types which also transition into more than one LUCC type. Hence, the statistical model is limited in its ability to project the full end-state land cover of a study area. The statistical model can however be useful when only one type of LUCC is of concern, such as urban expansion, deforestation, or reclamation. The proposed statistical model is especially useful to inform relevant land use stakeholders of the significant drivers of an LUCC they are concerned about and to show the future circumstance of the LUCC based on future values of these drivers.

In the future, studies can explore the calibration of global probability thresholds based on a different objective function. In the developed statistical model, global probability threshold values were derived using an optimization routine based on a GA that maximizes fuzzy kappa, a map comparison statistic which is on similarities in local neighborhood similarities. However, maximizing fuzzy kappa does not guarantee similarities in global value of the LUCC. In the future, LUCC studies can explore minimizing the ADP, which focuses on differences in global quantitative value, to find the optimal probability threshold. Examples of such studies may focus on simulation of future reclamation, mangrove extent change, or urbanization which focuses more on quantity prediction.

7. Conclusions

This paper developed a statistical model for simulating LUCC by integrating a logistic model based on spatial explanatory variables that generates a probability map and a linear model based on non-spatial explanatory variables that generates a global probability threshold. Previous LUCC models integrated an allocation module based on a logistic model with a demand module such as systems dynamics to compute a quantitative value of LUCC based on non-spatial explanatory variables. These allocation-demand models can produce accurate maps but are too complex to develop if a list of significant non-spatial explanatory variables should be included in a model. The developed statistical model adopts a simple pattern-based approach where non-spatial explanatory variables are incorporated in simulating LUCC by relating these non-spatial variables to a global probability threshold through a linear model. By comparing the pixel values in the probability map with the global probability threshold, maps of LUCC occurrence can be simulated. To derive optimal probability thresholds for linear regression, optimization through a GA was implemented that will maximize the Fuzzy Kappa or neighborhood similarities between simulated and actual maps.

The statistical model was applied in a watershed in the Ifugao rice terraces, Philippines to simulate the occurrence of agricultural abandonment. Results showed that slope, cosine aspect, quickflow, distance to town center, distance to road, world heritage site status, forest density, low vegetation density, and paddy field density were significant determinants of the local probabilities of agricultural abandonment while total forest area, five-year average precipitation, and average daily maximum temperature were significant determinants of the global probabilities of agricultural abandonment. Accuracy assessment of the simulated maps showed satisfactory accuracies for LUCC simulation applications. This confirms that the developed statistical model that uses time-series trends of spatial and non-spatial explanatory variables can be utilized to simulate future LUCC.

The developed statistical model brings forward the field of LUCC modeling by providing land use scientists and planners with another option in modeling and simulation with its capability to identify the significant spatial and non-spatial driving factors of LUCC and use these factors for future simulation. In future research, derivation of global probability thresholds based on optimization can be geared towards minimizing ADP to align simulated quantitative value of LUCC to actual quantitative values. Coupling the statistical model with simulation models to simulate LUCC based on future values of explanatory variables can also be explored.

CRediT authorship contribution statement

Ian Estacio: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing – original draft, Visualization, Funding acquisition. **Corinthias P.M. Sianipar:** Methodology, Writing – review & editing, Visualization. **Kenichiro Onitsuka:** Methodology, Supervision. **Mrittika Basu:** Methodology, Supervision. **Satoshi Hoshino:** Conceptualization, Supervision, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary material

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