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Land use and land cover change implications on agriculture and natural resource management of Koah Nheaek, Mondulkiri province, Cambodia

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ABSTRACT

Monitoring and mapping land use and land cover (LULC) changes is crucial for determining plausible resource availability in the future, and for providing policy implications towards the landscape's sustainable management. The LULC changes brought by economic land concessions and high deforestation are common issues in Koah Nheaek of the Mondulkiri province, distressing the sustainability of linked natural resources and agroecosystems. Determining its landscape's occurred changes and projection are vital inputs to succeeding policy programs as Koah Nheaek implements the Rectangle 4 (i.e., inclusive and sustainable development) of the Rectangular Strategy Phase IV (2018-2023). In this study, the LULC changes (2000-2020) in Koah Nheaek were analyzed using Google Earth Engine (i.e., the random forest). Corresponding to the LULC dynamics concept, forest had the highest loss (37% change) while wood shrub, grassland, orchard, and agriculture land gained a significant increase. In addition to the loss during the last 20 years, the forest was again degraded about 16% based on the 2030 projection using Markov-CA model. On the other hand, using General Linear Method, the trajectories and projection were supported by the inputs from focus group discussion of stakeholders. For this regression analysis, significant factors influencing decisions for current and future agricultural expansion included the household size and the inheritable parcel size. Upon this biophysical and social evidence, the Rectangle 4 implementation is recommended to be strictly enhanced to achieve its goals. This study suggests sustainable land measures (Good Agricultural Practices, Climate Smart Agriculture, Comprehensive Land Use Planning, and Agroforestry) to balance and manage land uses as a key to sustainability.

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1. Introduction

Nowadays land use and land cover (LULC) changes are crucial within the study and analysis of crafting a sustainable plan of land uses, as their data availability shows the landscape's trends through the years linking the availability of resources with anthropogenic needs and demands. Thereby, knowing the LULC trends and projection is vital for providing critical input to decision-making on sustainable ecosystem management and environmental development in the future (Zhao et al., 2004; Dwivedi et al., 2005; Ellis and Pontius, 2007; Fan et al., 2007).

Over the last few decades in Cambodia, underlying driver components such as policies and property rights, the economy and markets, and population dynamics have wrought changes in the country's LULC while imprinting such history on the landscape (Xing, 2013; Trzcinski and Upham, 2014; Hak et al., 2018). Evidently in the post-war period in the 1990s, large-scale forest concessions under the 1992 Land Law have been promoted, as the state was transitioning towards a market-oriented democratic state (Trzcinski and Upham, 2014). This resulted for the agricultural land to increase in expense of forest loss (Trzcinski and Upham, 2014; Hak et al., 2018). Meanwhile, when the 2001 Land Law was enacted, new property rights were named in categories of: State Public Land, State Private Land, Economic Land Concessions (ELCs) and Communal Land Titles, that promoted the goal of provisioning greater tenure security to average Cambodians. However, these caused confusions over the property rights on communal land of the indigenous people (IP) and economic land concessions (Hak et al., 2018). To detail accordingly, communal land was largely overlapped with the ELCs, that was previously categorized as State Public Land, but was eventually reassigned as State Private Land and was invested by foreign and domestic investors through the ELCs (Trzcinski and Upham, 2014; Hak et al., 2018). And this property rights issue between the ELCs and IP communities was largely prominent in the country's northeastern provinces, including the Mondulkiri province.

The Mondulkiri province is blessed with rich natural and wildlife resources which theIP and Khmer communities rely on. Currently, these natural resources in the province are alarmingly decreasing due to the pressures from commercial land clearance, agricultural expansion, and predominant ELCs (Watkins et al., 2016; SNEC, 2007). This situation resulted to rampant deforestation on the IP territories as large areas of forest are being converted into a large-scale extensive plantation of rubber, cassava and cashew due to the ELCs implementation while leaving the IP no choice but to adapt to the situation of making them reliant on volatile cash crop markets and precarious wage work (Hak et al., 2018). And with the deforestation and forest degradation occurring in the province, the forest that the IP considered as a crucial natural resource cannot give them its ecosystem services unlike before (Watkins et al., 2016). In addition, the slumping cash crop prices in 2018 implied reduction of the resiliency of the IP livelihood and essential well-being as there was a loss of diversity of livelihood that was also primarily brought about by deforestation and forest degradation as mentioned (Hak et al., 2018). Meanwhile, in-migrants from different provinces to the Mondulkiri province also caused increased agricultural land and illegal trade in luxury wood (Watkins et al., 2016; SNEC, 2007). These, including shifting cultivation, have been prominent in Koah Nheaek of the Mondulkiri province. Various literatures mentioned that shifting cultivation and swidden farming are the mostly found activities on the uplands of Mekong Region and Southeast Asia that promote unsustainable the LULC changes (Xing, 2013; Padoch et al., 2007; Rowcroft, 2008). And imbalance on the land uses with the occurring forest degradation can result to negative implications on the flow of ecosystem services across the landscape, and eventually affect the communities therein (Watkins et al., 2016).

As most of the communities rely on agriculture and natural resources, it is important to consider the environmental and agricultural sector as providers for the basic needs of the people. Land practices and their management further create various LULC patterns that can either be harmful or beneficial to other ecosystems (Kanianska, 2016). Out of the three districts and one town of the Mondulkiri province, Koah Nheaek has the larger percentage of communities that rely on the agriculture impacted by the ELCs, and especially represents the most forest degradation in Cambodia. In that case, even if the agricultural land continue expanding, this might have such partly negative implications on the production of the inputs to agroecosystems coming from the forest ecosystem services as they will be degraded. The forest ecosystem services are the providers of water and supporting services necessary for the regulation of the productivity of the soil (FAO, 2016). Moreover, if the country continues to be more developed in the future, this implies the increase in built-up area replacing further the agricultural land and forest while considering the probable increase in more ELCs. This in turn will further affect the sustainability of the country. With that, balancing the social, economic development and environmental health in terms of changing the land uses should be of a pressing need to be considered. An important way to achieve this is through transformative policies that are backed up with science-based actions. On the other hand, as the impact of the LULC changes on carbon dynamics, climate change, hydrology, and biodiversity have been recognized (Sohl and Sleeter, 2012), the modeling of their transformational forces has become increasingly important especially for detecting their changes at the multiple spatial-temporal scales (Saah et al., 2020).

As Cambodia's main livelihood and food security rely on the agricultural sector and natural resources, sustainable management of these areas have been considered important for the nation's development and have gained such attention from the policymakers recently (Frewer and Chan, 2014). This resulted for the inclusion of these components within the program of the Rectangular Strategy—in which it is part of the policy framework that is crucial for the implementation of the National Strategic Development Plan of 2019–2023 (RGC, 2018). As defined, the Rectangular Strategy- Phase IV (or namely, the Rectangle 4: inclusive and sustainable development) is the blueprint that guides the activities of stakeholders within the Dynamics of Stakeholder System, ensuring the efficiency and effectiveness of managing the resources (RGC, 2018). This study particularly focused on the Rectangle 4 that aims to: (1) Promote agricultural and rural development; (2) Strengthen sustainable management of natural and cultural resources; (3) Strengthen the management of urbanization; and (4) Ensure environment sustainability and readiness for climate change (RGC, 2018). To create better implementation measures on managing the agricultural realm and natural resources specifically on the target of the Rectangle 4, it is a need to consider the underlying factors and drivers of the LULC changes through time. As mentioned by Davis et al. (2015) and Schmidt-VogtDietrich (2009), the LULC studies will enable to provide precise to realistic estimates on the extent of land areas under a certain activity that will enable the policy makers to craft measures to address this issue occurring at a specific area. Through this, in-depth knowledge of the LULC changes will reduce poverty, improve livelihoods, and maintain ecosystem services (Watkins et al., 2016). As the study area has insufficient data, thus the analysis on the LULC changes can provide science-based recommendations for the betterment of the policy implementation and creation of viable measures. This current study will also serve as a baseline in determining the future pathways for the LULC transitions for the year 2030 that will aid in the betterment of policy implementation. Including the improvement of agriculture and natural resource management and balancing the land uses for inclusive and sustainable development, this will also help the IP communities be partners for forest protection and for Khmer communities to negate from unsustainable land uses. The IP and Khmer communities catalyze the achievement of the Rectangle 4. As such, this study mainly aims to improve the adaptive capacity of the agricultural sector in line with the natural resource management of Koah Nheaek District of the Mondulkiri Province in terms of the impact from the LULC changes. On the other hand, the specific objectives are to: (1) analyze the LULC changes in Koah Nheaek through 2000-2020 using Geographic Information System (GIS) and Remote Sensing; (2) determine the likely future pathways for the year 2030 for the LULC transitions in the study area; and (3) provide policy implications or recommendations for the likely future pathways in terms of a sustainable management of land use practices.

2. Methods overview

Six platforms were applied to analyze the LULC trends that provided the inputs for policy implications, involving the biophysical and social components (Fig. 1). For the biophysical component, USGS Landsat 5, 7, and 8 surface reflectance products of Google Earth Engine (GEE) were used to create a consistent time-series of the LULC within the landscape. This was deemed to be used in the study to suffice the lack of available data of the study area. A random forest method was used to train the data points from the land classes of 2000, 2010, and 2020. Stratified random sampling of the land classes was then subjected for accuracy assessment and validation of each land class through Collect Earth Online (CEO Version: prod-2022-07-11). The CSV file output was computed in the System for Earth Observation Data Access, Processing and Analysis for Land Monitoring (SEPAL; Also, see the detail in Gomes et al. (2020) for the classification error matrix using the confusion matrix. Through the accuracy assessment process, the LULC 2020 as an input for projection stage was validated. TerrSet 18.31 was then used for projection, with the attributes of driver variables acquired from the focus group discussion (FGD) and Key Informant Interview (KII) for the future decisions on land uses. Transition matrices for projection were visualized using Markov-CA model, generating the LULC map for the year 2030. The generated LULC maps for the years 2010, 2020, and 2030 were subjected for the LULC area estimates and tabulation. For a holistic approach, social component visualizing the historical trends of the LULC changes was also exhibited through the FGD and KII that provided implications for the Rectangle 4.

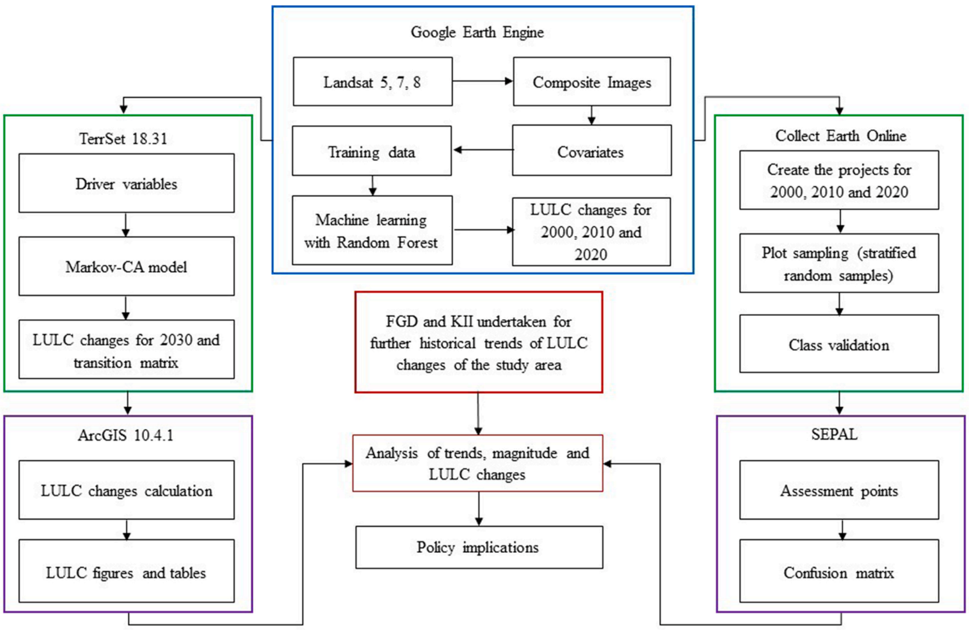

Fig. 1. General methodology of the study area.

3. Study area

The study site is Koah Nheaek of the Mondulkiri Province (Fig. 2), located in the Northeastern part of Cambodia, and bordered by the Ratanakiri and Steung Treng provinces along the north, the Kratie Province in the southwest, and Vietnam to the east. The study area has a total land area of 52,827,849 ha and total population of 22,026 people, that comprises of 5171 households (Police Inspection Department of Koah Kheaek, 2020). It is further subdivided into 6 communes (Or Buon Leu, Srae Sangkum, Nong Khi Lik, Raya, Srae Huy and Sok Sant) involving some IP communities, and mainly relying on agriculture and natural resources for livelihood. The study area is generally classified to have dense forest (Watkins et al., 2016) and harbors rich biodiversity, and natural resources. However, it is experiencing high rates of deforestation, economic land concessions, and agricultural expansion (Watkins et al., 2016).

4. Classification of the LULC and accuracy assessment

4.1. Training data

The remote sensing composites (30 m × 30 m) (i.e., Landsat 5, 7 and 8) were acquired through SERVIR-Mekong. The latter is a geospatial data-for-development program that responds to the needs of the Lower Mekong countries. The image composites were used to generate the land classes for the reference data adopted from Saah et al. (2020) and Poortinga et al. (2020) for the years 2000, 2010, and 2020. Those authors calculated the medoids (i.e., in 20th and 80th percentile for each year) after removing cloud and the shadow, and applying topographic correction (Saah et al., 2020).The points for each class have been identified through the GEE interface to test the usability and reliability of the entire procedure. Eight land classes and the corresponding number of training data per class are included in the reference data and were subjected to the random forest method within the GEE. These land classes and their corresponding descriptions and points are shown (Table 1).

4.2. Training and validation of the land classes

For validation process, each class was created using stratified random sampling from the GEE depicting the categories of changes for the years 2000, 2010 and 2020. In this case, the 100 random stratified points were generated per class. The buffer was prepared with a fixed radius (15 m), created around each point. These were then imported as CSV files to prepare for new tables for longitude and latitude, and the variables renamed as PLOTID and SAMPLEID.

In this study, validation of the LULC maps with three projects was created on the CEO platform for the years 2000, 2010 and 2020. The CEO is a new, free open source and user-friendly software tool for land monitoring (see, https://collect.earth/) (Saah et al., 2019). To ensure that the training points produced sufficient samples of each class for interpretation, the approach of stratified random sampling was implemented. The results from the CEO were analyzed using the stratified estimator-analysis tool in the SEPAL

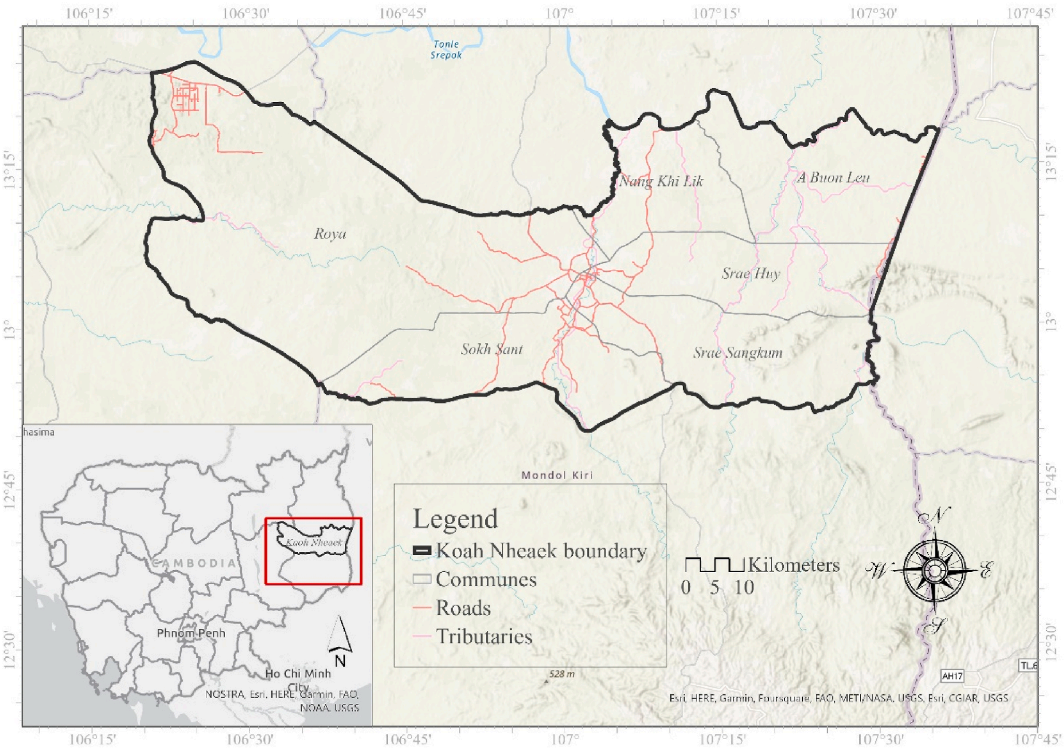

Fig. 2. Location of the study area.

Table 1
Description of land classes and training points used for the three years 2000, 2010 and 2020.

LULC classes	Description	Training points
Forest	Protected forest, forest on customary land and flooded forest	200
Agricultural land	All cultivated agricultural land (e.g, % of land area), which majority involves rice fields.	330
Water body	It is an open water larger than 30 m by 30 m that is open to the sky. In Koah Nheaek, the common water bodies are rivers, water, ponds, and reservoirs.	200
Built-up area	Broad classification of socioeconomic infrastructure such as residential, commercial and service, industrial, and others.	250
Wood shrub	Land areas covered by sparsely grown short thorny trees and bush, and also described with a mixture of low woody (e.g., forest regeneration) and non-woody vegetation that is typically transitional in nature, occurring after either agricultural abandonment or deforestation.	285
Grassland	Areas with herbaceous cover of grasses, in which comes as the result of deforestation. In other words, grassland in the area is not natural formed but is due to the consequence of conversions from forest to other land uses and are left barren. This class also includes the barren land.	240
Orchard plantation	Areas cultivated with perennial crops (rubber, mango, cashew nut and cash crop the land for long periods). This also includes the ELCs.	265
Wetland	Seasonally flooded regions in lowland areas and usually dominated by grass vegetation.	170

(https://sepal.io/) to display an accuracy statistics (FAO, 2022). The SEPAL includes confusion matrix, area estimates, and a graph of these area estimates with confidence intervals for the three mentionned years.

4.3. Accuracy assessment of the LULC

Accuracy assessment of the LULC classification was implemented for the years 2000, 2010, and 2020 within the GEE. Measures derived from the error matrices involved overall accuracy and Kappa coefficient. In addition, Producer's accuracy and User's accuracy were also obtained for each class, that respectively measured the commission and omission errors (Olofsson et al., 2013, 2014, 2020). The value of overall accuracy greater than 0.70 is regarded as an acceptable classification accuracy (Lillesand et al., 2015). For most applications, value of Kappa coefficient that is more than 0.75 can be accepted as an excellent or very good agreement while values in the range of 0.40–0.75 are indicative of fair or good correspondence, and value less than 0.40 represents poor correspondence (Fleiss et al., 2013).

5. LULC projection

5.1. Markov-CA model of the TerrSet

To signify the LULC projection brought by continuous data influenced by the driver variables, the TerrSet Land Change Modeler was applied in this study, that is similarly applied based on related studies on land cover change projection (Lu et al., 2019; Girma et al., 2022). Specifically, this study used Markov-CA model of the TerrSet (Clark Labs Software IDRISI version 18.31) to analyze and predict the future LULC. Early LULC maps of 2010 and 2020 served also as basis input in the model for depicting the transition probability matrix records to project the 2030 LULC map. As adopted from the works of Singh et al. (2015), application of the model is hinged on the random process number X (t), provided that the Markov-CA model process for the time is $t1 < t2 < \ldots < tn < tn+1$. With this, the random process equation is:

$$Fx(X(tn+1) \leq xn+1 \mid X(tn) = xn, X(tn\text{-}1) = xn\text{-}1, X(t1) = Fx(X(tn\text{-}1) \leq x\ n\text{-}1 \mid X(t1) = xn) \tag{1}$$

where: tn represents the current time; tn + 1 corresponds to some points in the future; and t1, t2, …, tn−1 denotes various points in the past. Based on the present data, this represents the independency of the future's random process from the past. This is given that the Markov-CA model process is represented through X[k], with the states of {x1, x2, x3, …}. Thereby, the transition probability of state i to j for such term is:

$$Pi,j\ \mathrm{Pr}(X[K+1] = j \mid X[K] = I \tag{2}$$

5.2. Driver variables selection

As defined, driver variables serve as factor representatives that influence the LULC changes (Chim et al., 2019; Megahed et al., 2015). These are imperative for predicting the changes accurately, transcending its importance on the critical selection of such input driver variables. Given this, FGD and KII implemented provided the possible biophysical drivers of changes based on the historical land uses of the study area. The driver variables identified were elevation, slope, and topography that are also evidenced and validated with the relevant literatures. For elevation and slope, it was mentioned that these are useful biophysical variables similarly used for predicting the patterns of deforestation in rural areas (Kim et al., 2014; Lambin, 1997). While topography implies the influence of the continuous forest conversion and its possible extent. In such manner, literatures (Girma et al., 2022; Sader and Joyce, 1988; Wubie et al., 2020; Leta et al., 2021) found that deforestation decreases as slope gradient increases shown (Table 2).

With the specified driver variables, elevation and slope were generated from SRTM Digital Elevation Data Version 4 from the GEE. The significance of driver variables was tested using Cramer's V and P values that measure strength of the correlation between two

Table 2
Data layers used in the Markov-CA model for the year 2030.

Layers	Spatial Resolution (m)	Temporal Resolution	Description	Reference
Distance to building	30	Single	OSM	https://www.openstreetmap.org
Distance to roads	30	Single	OSM	https://www.openstreetmap.org
Land cover map	30	Yearly	LULC	https://earthengine.google.com
DEM	30	Single	SRTM	https://earthengine.google.com
Slope	30	Single	SRTM	https://earthengine.google.com

variable classes. To define, using Cramer's V and P values do not assure a strong performance of the variables since it cannot represent the scientific prerequisites and the multifaceted nature of the relationships. However, it only assesses the viability and significance of a variable to be included as among the driver factors of LULC changes (Hasan et al., 2020).

6. Social component of LULC changes

The FGD and KII were implemented to determine the underlying causes of LULC changes to provide holistic perspective of thier patterns, and their probable trajectories. For the KII, six communes comprising the whole Koah Nheaek were surveyed. Stakeholders identified for each commune are the farming communities that were categorized to the IP and Khmer farmers. The sample size of the survey was determined following (Hailu et al., 2020):

$$n = \frac{z^2 * p * q * N}{e^2 (N - 1) + z^2 * p * q} \tag{3}$$

where n is the sample size; z is the 95-confidence limit (interval) under normal curve that is 1.96;

p is the 0.1 (proportion of the population to be included in this study that is 10%);

q is the nonoccurrence of event = 1–0.1 that is 0.9; N is the total number of households, that is 5171; and e is the margin of error or degree of accuracy (accepted error term), that is 0.05. Hence, distribution of the farmer respondents for the KII was shown (Table 3).

Prior to the data collection, the questionnaire was pre-tested to determine the question's suitability with the limited time and its efficiency to collect important information. The 135 household heads were selected randomly from each sampled commune to participate in in-depth interviews. Prior informed consent was also given to the respondents before the interview. Data collected from questionnaire were then coded and categorized into a suitable data entry format and analyzed using the Generalized Linear Model (GLM) with R −4.0.1 (Team, 2013). The variables used in the models for the GLM (Table 4) with their corresponding description are shown below.

Table 3
Distribution of sample size relative to the communes for the year 2020.

Name of communes	Number of household per commune	Agricultural land (ha)	Sample size
Or Buon Leu	478	1950	12
Srae Sangkum	1675	6838	44
Nong Khi Lik	828	4195	22
Raya	661	85,120	17
Srae Huy	657	2460	17
Sok Sant	872	2124.05	23
Total	5171	102,687.05	135

Table 4
Variables and their description for the Generalized Linear Model (GLM).

Variable codes	Description
Dependent variable	
fttenyr_n	Future size of the parcels for the next 10 years: Area of the parcels that is predicted to be acquired per household for the next 10 years (0 = 1–5 ha, 1 = 7 up ha)
Independent variable	
hnber_n	Number of household member: People live in a household (numbers)
Sizeofland	Size of the parcels (ha in each household that they currently have)

7. Results

7.1. Identifying the LULC changes

7.1.1. LULC accuracy assessment

Accuracy assessment of the LULC classification (Overall accuracy, Kappa coefficient, Producer's accuracy and User's accuracy) was implemented to validate the eight land classes for the years 2000, 2010, and 2020. The results from validation shown (Table 5) fit well with the datasets of the study area. Accuracy values for the years 2000, 2010, and 2020 based on overall accuracy were espectively 0.87, 0.84, and 0.85 while the Kappa coefficients were 0.85, 0.82, and 0.82. Likewise, accuracy levels of each land class were shown based on the percentage of Producer's accuracy and User's accuracy, demonstrating the compatible results of the LULC over various periods.

7.1.2. LULC changes and classification

The LULC classes for the years 2000, 2010, and 2020 classified through the GEE, and the projected LULC map for the year 2030 were determined using TerrSet demonstrated the following extent (km^2) (Table 5). Since 2000, forest (2668.95 km^2; 50.53%) has the largest extent of cover followed by wood shrub (1735.36 km^2; 32.85%), grassland (1735.36 km^2; 32.85%), agricultural land (137.22 km^2; 2.60%), orchard plantation (112.809 km^2; 2.14%), and built-up area (17.54 km^2; 0.33%) (Table 6; Table 7). Through the 20-year period (2000-2020), forest incurred the highest cover loss (−37%) while wood shrub (14.34%), orchard plantation (11.02%), grassland (9.09%), and agricultural land (2.01%) gained the significant increase. Based on the probable change (2020-2030) from the predicted LULC for the year 2030, forest, agricultural land, and wetland will continue to decrease by 2.93%, 0.42%, and 0.01%. On the other hand, orchard plantation will continue to increase by 3.36% while other land classes will have no significant changes (water body, built-up area, wood shrub, and grassland).

In terms of trends, forest was converted into wood shrub, orchard plantation, grassland, and partly agricultural land from 2000 to 2010 (Fig. 3). Likewise, from 2010 to 2020, forest was converted to similar mentioned land classes—largely into orchard plantation, wood shrub, and smaller parts on grassland and agricultural land. And as projected for the year 2030, more forest will decline along-

Table 5
Accuracy assessment of the LULC maps in Koah Nheaek for the years 2000, 2010, and 2020. PA stands for Producer's accuracy. UA stands for User's accuracy.

Error matrix: 2000											
Overall accuracy = 0.87, Kappa coefficient = 0.85											
LULC classes	F	A	WB	BU	WS	GL	OP	WL	Total	PA%	UA%
Forest (F)	90	0	0	0	10	0	0	0	100	0.87	0.90
Agricultural land (A)	1	91	0	0	0	8	0	0	100	0.96	0.91
Water body (WB)	0	0	92	0	1	2	0	5	100	0.98	0.92
Built-up area (BU)	0	3	0	78	3	11	5	0	100	0.99	0.78
Wood shrub (WS)	1	0	0	0	89	10	0	0	100	0.74	0.89
Grassland (GL)	0	0	0	1	15	84	0	0	100	0.65	0.84
Orchard plantation (OP)	11	0	0	0	0	3	86	0	100	0.95	0.86
Wetland (WL)	0	1	2	0	3	12	0	82	100	0.94	0.82
Total	103	95	94	79	121	130	91	87	800		
Error matrix: 2010											
Overall accuracy = 0.84, Kappa coefficient = 0.82											
LULC classes	F	A	WB	BU	WS	GL	OP	WL	Total	PA%	UA%
Forest (F)	86	0	0	0	14	0	0	0	100	0.78	0.86
Agricultural land (A)	0	92	0	0	0	7	1	0	100	0.95	0.92
Water body (WB)	0	2	85	0	0	5	0	8	100	0.98	0.85
Built-up area (BU)	0	3	0	81	2	8	6	0	100	1.00	0.81
Wood shrub (WS)	2	0	0	0	87	11	0	0	100	0.69	0.87
Grassland (GL)	0	0	0	0	22	78	0	0	100	0.66	0.78
Orchard plantation (OP)	22	0	0	0	0	3	75	0	100	0.91	0.75
Wetland (WL)	0	0	2	0	2	7	0	89	100	0.92	0.89
Total	110	97	87	81	127	119	82	97	800		
Error matrix: 2020											
Overall accuracy = 0.85, Kappa coefficient = 0.82											
LULC classes	F	A	WB	BU	WS	GL	OP	WL	Total	PA%	UA%
Forest (F)	86	0	0	0	14	0	0	0	100	0.84	0.86
Agricultural land (A)	0	93	0	0	0	6	1	0	100	0.96	0.93
Water body (WB)	0	0	88	0	0	0	0	12	100	0.98	0.88
Built-up area (BU)	0	3	0	77	4	12	4	0	100	1.00	0.77
Wood shrub (WS)	2	0	0	0	95	3	0	0	100	0.69	0.95
Grassland (GL)	0	0	0	0	23	77	0	0	100	0.65	0.77
Orchard plantation (OP)	13	1	0	0	0	13	73	0	100	0.94	0.73
Wetland (WL)	1	0	2	0	2	8	0	87	100	0.88	0.87
Total	102	97	90	77	138	119	78	99	800		

Table 6
Extent of land classes for the years 2000, 2010, 2020, and 2030 in km^2. MLP stands for multilayer Perceptron. Forest (F), Agricultural land (A), Water body (WB), Built-up area (BU), Wood shrub (WS), Grassland (GL), Orchard plantation (OP), Wetland (WL).

										Overal accuracy
Year	F	A	WB	BU	WS	GL	OP	WL	Kappa	MLP
2000	2668.95	137.22	23.76	17.55	1735.36	577.27	112.81	9.33	0.85	–
2010	1402.62	172.48	37.33	35.71	2267.31	848.38	502.08	16.34	0.82	–
2020	869.24	265.20	27.30	42.15	2492.91	1057.40	517.66	10.38	0.82	–
2030	714.34	243.24	27.30	42.15	2492.91	1057.40	695.12	9.78	–	0.44

Table 7
Extent of land classes (%) and their changes per period (km^2; %).

LULC classes	Extent of land classes				Changes per year						
	2000	2010	2020	2030	km^2	km^2	km^2	%	%	%	%
	%	%	%	%	2000–2010	2010–2020	2020–2030	2000–2010	2010–2020	2000–2020	2020–2030
Forest (F)	50.53	26.55	16.46	16.02	−1266.33	−533.38	−154.90	−23.97	−10.10	−37.00	−2.93
Agricultural land (A)	2.60	3.27	5.02	5.49	35.26	92.72	−21.96	0.67	1.76	2.01	−0.42
Water body (WB)	0.45	0.71	0.52	0.52	13.57	−10.03	–	0.26	−0.19	0.07	–
Buit-up area (BU)	0.33	0.68	0.80	0.80	18.16	6.44	–	0.34	0.12	0.47	–
Wood shrub (WS)	32.85	42.92	47.19	47.19	531.95	225.60	–	10.07	4.27	14.34	–
Grassland (GL)	10.93	16.06	20.02	20.02	271.11	209.02	–	5.13	3.96	9.09	–
Orchard plantation (OP)	2.14	9.51	9.80	9.80	389.27	15.59	177.45	7.37	0.30	11.02	3.36
Wetland (WL)	0.18	0.31	0.20	0.16	7.01	−5.96	−0.59	0.13	−0.11	0.01	−0.01

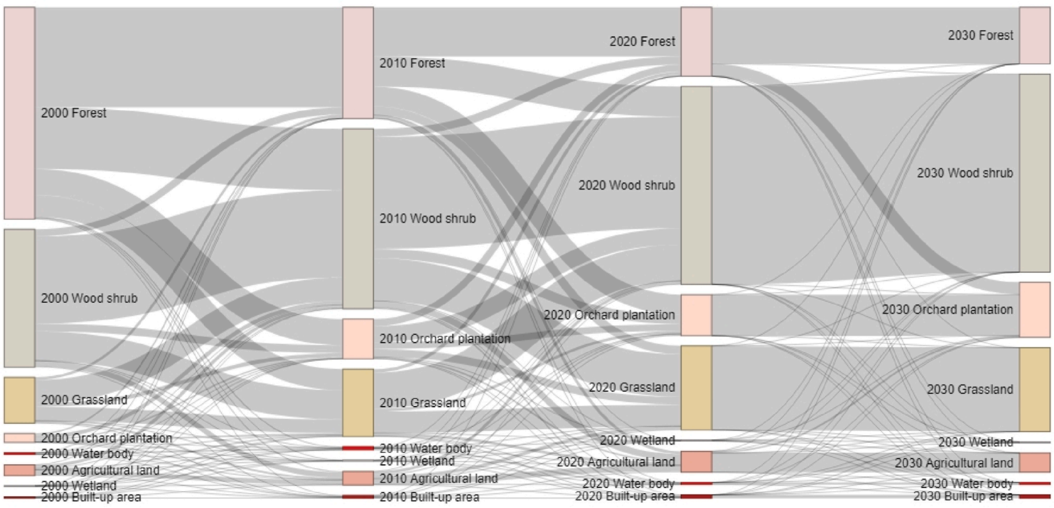

Fig. 3. Sankey plot of the LULC changes of the study area.

side with the increase in orchard plantation and small increment in agricultural land. Patterns of LULC changes across the period demonstrated such changes (Fig. 4).

7.2. Predicting the future LULC for the year 2030

7.2.1. LULC transition probability analysis

Transition probability matrix was produced for the year 2030 using 2010 and 2020 LULC changes (Table 8). This matrix showed the probability of a conversion for each LULC change to another class, within the specified time. Such revealed the significant probabilities of transition between two different time periods (2020-2030). Forest will be likely to be converted into classes of wood shrub, orchard plantation, grassland, and agricultural land with the probabilities of 0.270, 0.178, 0.075, and 0.027; respectively while the probabilities that portions of the eight classes will remain the same were about 0.443 (F), 0.428 (A), 0.531 (WB), 0.130 (BU), 0.622 (WS), 0.320 (GL), 0.168 (OP), and 0.140 (WL).

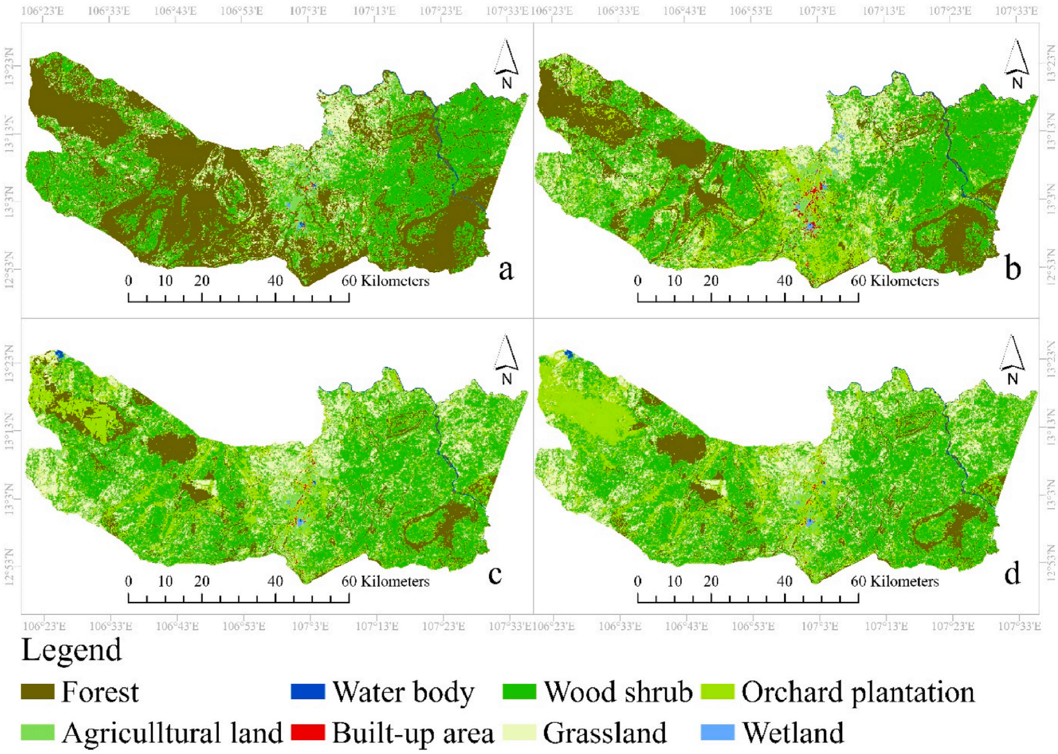

Fig. 4. LULC distribution in the study area (a) 2000, (b) 2010, (c) 2020, (d) 2030.

Table 8
Transition probability matrix of the LULC changes for the year 2030.

LULC classes	Probability changes							
	F	A	WB	BU	WS	GL	OP	WL
Forest (F)	0.443	0.027	0.003	0.003	0.270	0.075	0.178	0.002
Agricultural land (A)	0.007	0.428	0.002	0.039	0.210	0.228	0.083	0.004
Water body (WB)	0.290	0.014	0.531	0.001	0.046	0.025	0.069	0.023
Built-up area (BU)	0.011	0.362	0.001	0.130	0.133	0.095	0.260	0.008
Wood shrub (WS)	0.045	0.036	0.001	0.007	0.622	0.236	0.053	0.001
Grassland (GL)	0.050	0.041	0.001	0.007	0.538	0.320	0.041	0.001
Orchard Plantation (OP)	0.178	0.042	0.001	0.008	0.406	0.195	0.168	0.002
Wetland (WL)	0.129	0.192	0.048	0.010	0.122	0.303	0.057	0.140

7.2.2. Driver variables of LULC change projection

Delving into the set of driver variables that determined the changes in land classes for the projection, this study selected relevant variables – among others, the distance to roads, DEM, distance to built-up area, and all to orchard plantation based on their explanatory values using Cramer's V and P values (Table 9). To define, the Cramer's V does not give decisive proof that a particular variable explains the LULC changes. However, it is rather a more intuitive tool that can be utilized to understand the significance that a particular variable has an influencing change. All the variables are significant as their P values are less than 0.01 level (Table 8). This result revealed that the road distance and elevation are the major explanatory variables and imperative topographic factors that influenced such projection.

Table 9
Cramer's V and P values for each of the explanatory variables.

Variables	Cramer's V
Distance to roads	0.3534
DEM	0.3534
Distance to building	0.3061
All to orchard plantation	0.2358

7.3. Social component variables of LULC trends

7.3.1. Regression results of models

There were seven models to determine the correlation among selected variables. Results revealed that all models have significant variables ($P < 0.05$) while model 4 acquired the lowest Akaike Information Criterion (AIC) value of 162.0, and Bayesian Information Criterion (BIC) value of 173.6, implying its strong, positive, and high correlation among other models. Similarly, based on the validation on the accuracy levels (Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), Multinomial Logistic Regression (MLR), and Generalized Linear Model (GLM)), model 4 acquired the highest accuracy (0.687-LDA, 0.688-QDA and 0.694-MLR, and 0.700-GLM; respectively) among the models (Table 10). It also showed a 0.56 probability of increase in land conversion over time as specified on the response—based on the Root Mean Square Error (RMSE) in which implied that the prediction was close to actual value, indicating a better predictive accuracy (Table 11). This showed that the importance of the variable's ranking in defining the most influencing variables from all key variables, instead of choosing one best model. In this way, more options are available for monitoring and restoration actions.

7.3.2. Profile of the respondents

Frequency of respondents per commune surveyed is shown (Table 12). In order to provide for their household, all of the farmers are implementing subsistence farming while 91.85 have the cases of conducting production farming at the same time, and 0.74 cases of applying as hired labor for other farmers to increase their income (Table 13). This was based on a multiple response to know the

Table 10
Models (and corresponding variables) affecting the decision of farmers on increasing land uses of the study area. A *P*-value less than 0.05 is statistically significant.

Models	Rank	Df.res	AIC	AICc	BIC	McFadden	Cox and Snell	Nagelkerke	P-value
1	4	131	163.30	163.80	177.8	0.15	0.18	0.24	3.340 x 10-6
2	3	132	162.40	162.70	174.0	0.14	0.17	0.23	1.417 x 10-6
3	3	132	171.10	171.40	182.7	0.09	0.12	0.16	1.069 x 10-4
4	3	132	162.00	162.30	173.6	0.14	0.18	0.24	1.125 x 10-6
5	2	133	171.20	171.40	180	0.08	0.10	0.14	6.575 x 10-5
6	2	133	169.40	169.60	178.1	0.09	0.12	0.16	2.520 x 10-5
7	2	133	172.30	172.50	181.0	0.08	0.10	0.13	1.168 x 10-4

Table 11
Cross-validation accuracy of models and variables to estimate the error rate.

Models	LDA	QDA	MLR	GLM	RSME	Probability changes
1	0.673	0.673	0.658	0.670	1.309	0.521
2	0.688	0.703	0.688	0.690	1.297	0.476
3	0.636	0.643	0.622	0.640	1.162	0.337
4	0.687	0.688	0.694	0.700	1.294	0.563
5	0.630	0.630	0.630	0.630	1.138	0.268
6	0.651	0.658	0.658	0.670	1.155	0.359
7	0.660	0.660	0.660	0.660	1.134	0.610

Table 12
Communes surveyed in Koah Nheaek of the Modulkiri province.

Communes	Frequency	Percent	Male	Female
			Frequency	Frequency
Orbun	11	8.15	1	10
Srae Sangkum	45	33.33	21	24
Kiloek	22	16.3	7	15
Srae huy	17	12.59	6	11
Rayor	17	12.59	11	6
Soksant	23	17.04	8	15
Total	135	100	54	81

Table 13
Main income of household respondents.

Sources of income	Frequency	Responses	of the cases
Subsistence farming	135	51.92	100
Production farming (for selling)	124	47.69	91.85
Farming as laborer	1	0.38	0.74
Total		100	192.59

number of cases of farmers conducting the same activities. The average number of the respondent's household members comprises 5 people, with the range from 1 to 12 people per household as minimum and maximum (Table 14). While the respondents interviewed were only 20–82 years old, with the average age of 43 years (Table 14). In terms of parcel characteristics, the number of parcels of the respondents ranged from 1 to 5, with an average size of 3.81 ha (Table 14). The respondents were also asked on their desired parcels to be acquired for the next 10 years (8.12 ha) and the parcel areas that they would be willing to give to their children (2.33 ha) (Table 14). Moreover, there were farmer respondents who are migrants, coming from different provinces shown (Table 15). Among of their rationale on moving to Koah Nheaek were primarily due to livelihood (65.79), marriage (21.05), and other family matters (13.16) shown (Table 16).

8. Discussion

8.1. LULC trends from 2000 to 2020

8.1.1. LULC accuracy assessment

The more recent LULC map accuracy results were higher, and these may be related to a higher spatial resolution of satellite images (Fichera et al., 2012; Singh, 2010; Ahmad and SinghAhmad, 2017). According to Sitthi et al. (2016), the LULC map accuracy was quantified by creating an error matrix or a confusion matrix, that compares the classified map with a reference map. Accuracy assessment is essential for the individual classification if the classification data is to be useful in change detection (Conglaton, 1991; Lillesand et al., 1994; Owojori and Xie, 2005; Morales-Barquero et al., 2019). The overall accuracy of the LULC maps for the years 2000, 2010, and 2020 was higher than 0.83, that satisfied the suggested thresholds mentioned by Were et al. (2013) for the LULC maps with remotely sensed images, and thereby providing sufficiently evidence to investigate the LULC changes (Tran et al., 2015; Sourn et al., 2021). In this study, the overall accuracy levels of the LULC maps were highly around 0.85 for the three years (Table 5). Such levels were due to the types of resolution images in which literatures of previous studies confirmed (Lu and Weng, 2005; Mundia and Aniya, 2005; Nkomeje, 2017; Foody, 2020; Floreano et al., 2021). Accordingly, from these authors, the presence of mixed pixels is inherent in medium-spatial resolution images such as those used in this study, and similar with spectral confusion, which occurs when several land classes share a similar spectral response, thereby these mainly causes portions of inaccuracy. Although the Producer's accuracy and User's accuracy of land classes were below 0.65, the majority ranged from 0.65 to 100, that are acceptable accuracy levels for the complex nature of LULC changes. In this study, Koah Nheaek is influenced by the tropical monsoon climate. Therefore, the collected images were affected by clouds and their shadows, although the Landsat images made as a composite image at the GEE was used for pre-processing (Saah et al., 2020).

Table 14
Descriptive statistics of respondents' information and parcel characteristics.

Variables	Obs.	Mean	Standard deviation	Min	Max
age	135	43.55	13.12	20	82
Number of household members	135	5.04	2.17	1	12
Number of land of the respondents	135	1.74	1.03	1	5
Size of land of the respondents	135	3.81	3.85	0.8	35
Desired land areas to be acquired for the next ten years (ha)	135	8.12	8.13	0	50
Desired land areas to be given to children	135	2.33	1.81	0.3	10
Migrants	36	27.53	17.27	3	82
Resident of the area since birth	99	41.04	12.06	20	67

Table 15
Provinces the migrants came from.

Provinces	Frequency	Percent
Kampong Cham	20	55.56
Prey Veng	11	30.56
Takeo	1	2.78
Ratanakiri	1	2.78
Kratie	2	5.56
Svay Rieng	1	2.78
Total	36	100

Table 16
Rationale of the migrants for migration.

Rationale	Frequency	Percent
Livelihood	24	65.79
Marriage	7	21.05
Other family matters	5	13.16
Total	36	100

8.1.2. LULC classification and trends

The country traded its timber as such for currency with Vietnam to China (GIATOC, 2021). According to Yoeu (2016), the population increased in the Mondulkiri province in 2002–2012, from 40,194 to 70,439 people, that was primarily because of the demographic movement of people from lowland provinces. This was due to the better topographical conditions (compared with other lowland provinces) and the economic activity related to agricultural implementation, that made it possible for the encroachment in the uplands (i.e., Koah Nheaek) of the residents from the lowlands. Moreover, the presence of the ELCs were seen to be the other sources of livelihood of the in-migrants leading for the increase in built-up area for the 20-year period (18.16 km^2–6.44 km^2). Based on the KII, among the interviewed respondents who are in-migrants have an average of 27.53 years that have been living in the study area, in which this implies that the average of the respondents has immigrated before and within the year 2000. To detail, 55.56 of the in-migrants came from the Kampong Cham province and 30.56 from the Prey Veng province. The most common reason for in-migrants, owing to 65.79 was due to livelihood that were mainly subsistence farming. Also, in the same year, land economic concessions and illegal trade of timber were still occurring (Diepart and Schoenberger, 2016). For the LULC changes from 2000 to 2020, the analysis indicated that the forest, built-up area, wood shrub, grassland, orchard plantation, wetland, water body and agricultural land showed the most important LULC changes in the study area. As a result, the forest had the largest decrease of around 1266.33 km^2 from 2000 to 2010, and 533.38 km^2 from 2010 to 2020. On the other hand, the forest incurred such loss while wood shrub, and grassland increased over time that was primarily due to the illegal trade of timber in the study area. This was confirmed in the findings of Un (2017) and Milne (2015) in which illegal logging resulted to rapid deforestation leaving to primary forest to become secondary forest and wood shrub, implying the forest degradation resulting to unsustainable LULC changes. While the ELCs and agricultural land continued to increase as these are the main source of employment and the core of the rural economy, however resulted to deforestation (Magliocca, 2020). On the contrary, the ELCs were confirmed by Hak et al. (2018) and Haller (2016) to be the main hindrance towards sustainable development as the forest were converted into agro-industrial plantation (orchard plantation), in which has an underlying motive of commons-grabbing. Meanwhile, such land classes trends also have implications on neighboring land uses depicting connectivity of ecosystems (Rimal et al., 2019). As it has been identified that orchard plantation had lower increase of cover compared with wood shrub and grassland despite of the occurring ELCs, such was primarily due to the ended term period of the ELC contracts and the limited irrigation from the water body and wetland that were found to be decreasing over the 20-year period.

On the other hand, based on the FGD conducted, lesser increase in agricultural land compared with other land classes was due to the interest of some farmers to work in orchard plantation as they can acquire higher additional source of income other than the agriculture. While since agriculture is the main livelihood of the communities in the study area, portions of forest were also converted to agricultural land. This corroborates with the findings of Wasige et al. (2013) noting that the forest clearing occurring every year is mainly due to agricultural purposes—that is to increase parcels. However, other parcels were set aside for fallow and eventually became grassland through time. Similar with the findings of Kong et al. (2019), agricultural land increased tremendously from 1 percent in 1997 to 61 percent in 2016 across Cambodia, implying the continuous increase in agriculture brought by the decisions on the economy's focus.

8.2. Predicting the future LULC for the year 2030

8.2.1. LULC transition probability analysis

The Markov-CA model, a stochastic modeling process that simulates the future changes based on the past changes, was also used by Floreano et al. (2021) and Nath et al. (2018) in predicting the future land uses. Such matrix therein was produced by multiplying each column in the transition probability matrix with the number of cells of corresponding land uses in the image (Fig. 4).

8.2.2. Driver variables of LULC changes

Identified variables of the distance to roads and DEM as the primary variables influencing the changes depicted the suitability of forest to be converted to land classes that were used for livelihood and economic purposes (logging, agricultural land and orchard plantation) (Leta et al., 2021; Baqa et al., 2021). Likewise, previous studies of Leta et al. (2021) and Khoi et al. (2010) found that deforestation decreases with the increase in the slope gradient.

8.2.3. LULC prediction

The quantity of changes and the spatial distribution are the two components of LULC prediction in land change modeler (LCM) that are provided by Markov-CA model and Multilayer Perception (MLP) neural network (Hepinstall et al., 2008). The results of this study indicated by the MLP neural network's accuracy level (0.44) were identified to be at moderate level (0.41–0.60) based on the works of Landis and Koch (1977) that implied the suitability of the results in this current study. Similarly, another study of Floreano et al. (2021) revealed that such level type can obtain more-transition that better captures the LULC changes and their interactions found in the real environment.

8.3. Social component characteristics of LULC trends

8.3.1. Future land use pathway of the communities

Agricultural land and orchard plantation are among of the factors affecting the LULC changes. In terms of agricultural land, the percent of cases showed that all of the farmers are conducting subsistence farming. While aside from subsistence farming, the community respondents are also conducting farming for production and selling, as depicted by 91.85 of the cases. Both of these were primarily done by an average of 3 members in the household as labor. This is also the same with the findings of other studies (Chim et al., 2019) wherein these two factors (i.e., agricultural land and orchard plantation) cause the increased in the LULC trends. Other factors such as the ELCs as mentioned by articles have also been causing the increased in the LULC trends (Lu and Weng, 2005). It was emphasized that in 2001, the government established land law that allows two legal mechanisms to transfer the state-owned land (e.g., forest)—namely, the Social Land Concession (SLC) and ELCs. Accordingly, the SLC refers to the transfer of private state land for social purposes to the poor who lack land for residential and/or family farming purposes while the ELC grants are private state land that refers to a specific economic land concession contract for the concessionaire to use the area for agricultural and industrial agriculture purposes (Lu and Weng, 2005). With the seemingly benefit from the concessions, in-migrants to the uplands have increased based on the findings of Lu and Weng (2005), that is similar with the trends in Koah Nheaek. Such increase in in-migrants to the uplands consequently resulted to the increased demand for farmland and conversions of forest to the agricultural land and orchard plantation.

Various literatures (Munthali and Murayama, 2011; Munthali et al., 2019) further revealed similar findings that socio-economic variables served as determinants on rural communities' perceptions toward the LULC changes in their corresponding study area. Similarly, this study has identified that the result of Model 4 emphasized a low value of AIC and BIC used by the GLM, and therefore represents the best goodness-of-fit (Anselin, 1988; Burnhan and Anderson, 2002). This showed that the variables (i.e., the number of household members and size of land willing to provide for children) significantly influences the decision of the farmers on acquiring size of land. As such, the Khmer farmers tend to provide more land for their children. In most cases based on the presented results, the Khmer farmers (i.e., in-migrants) have acquired more land than the IP communities. This corroborates with various findings (Sourn et al., 2021; Kong et al., 2019; Neef and TouchJamaree, 2013; Baird, 2013) wherein encroachment of public land (such as forest, grassland and shrubland) occurs and causes for the displacements of the IP communities as the immigrants explored new farming. In addition, due to the increasing land prices, the IP communities tend to sell their land to the Khmer farmers and other immigrants pursuing the ELCs, that was also similarly discussed in the findings of Kong et al. (2019). Typically, land of the IP communities in the Mondulkiri province is made up of several separate areas (residential land, reserved land, sacred land, grave land, and farmland) where each receives a separate title due to the occurrence of communal land titling (CLTs) for indigenous community property (THOL and Il, 2019). However, the CLTs are seen to have consequences of land grabbing by the non-indigenous people to the IP communities, as emphasized by Landis and Koch (1977) and Munthali and Murayama (2011). While according to the study of Guérin (2012), land passed to their next generation increases the probability of the LULC changes that was similarly found in this study. This cycle continues and such land is further divided among the children for the coming generation, thereby increases the acquisition of agricultural land and orchard plantation, causing deforestation as implied in the scenario in Koah Nheaek that strengthened the point of this study.

9. Conclusions and policy implications

The forest decreased significantly over the last 20 years, whereas wood shrub, grassland, and orchard plantation had increased. Such trends confirm the land use dynamics concept, with underlying factors of policy, economic, and population dynamics, raising the demand for food, land, and promoting other sources of livelihood (ELCs, illegal logging, and shifting cultivation). In 2030, it was projected that forest cover will continue to decrease, signifying the unsustainable land practices will undoubtedly have negative effects on natural resources. The communities' significant variables influencing the future LULC decisions were the household size and the inheritable parcel size. As these social variables were also linked with the historical and future LULC trends, it is recommended for future policies to establish measures that will balance the components of sustainable development. And, as the Rectangle 4 has been implemented (2018-2023), it is crucial to align the recommended measures on good agricultural practices (GAP), climate smart agriculture (CSA), Agroforestry, and Comprehensive Land Use Planning (CLUP) for policy implications on inclusive sustainable development (Table 17). These measures will enable to improve the adaptive capacity of the agricultural sector in line with the natural resource management of Koah Nheaek. The GAP and CSA can cover the promotion of agriculture and rural development while ensuring the environmental sustainability and perceptive response to climate change. Agroforestry primarily targets the sub-indicators number 1, 2, and 4. These involve the encouragement for the farmer communities to engage in sustainable forestry, agroforestry, and fruit cultivation, that are more cost-effective and environmentally-friendly than illegal logging and shifting cultivation. Given that such land uses benefit the society as a whole, it is reasonable to provide the necessary support services and facilities to farmers who wish to engage in such land practices. While the CLUP targets all indicators by defining such land uses through the zoning. Combination of these recommendations can imply the achievement of Rectangle 4 in the future.

Author contributions

V. Teck and R. M. B. Legaspi conceptualized the study. For the biophysical component, V. Teck and A. Poortinga designed the methodology. The generated maps from the GEE and TerrSet were run by V. Teck based on the instructions and guidance of A. Poortinga, K. Dahal and C. Riano. V. Teck, A. Poortinga, K. Dahal, C. Riano, and V. Ann validated the maps. For the social component,

Table 17
Alignment of recommended measures to the Rectangle 4 (Inclusive and Sustainable Development) of the Rectangular Strategy.

Rectangle 4	GAP and CSA	Agroforestry	Comprehensive land use planning
1.Promotion of agriculture sector and rural development	✓	✓	✓
2.Sustainable management of natural resources and culture		✓	✓
3.Strengthening urban planning and management			✓
4.Ensuring environmental sustainability and perceptive response to climate change	✓	✓	✓

V. Teck and R. M. B. Legaspi designed the questionnaire, reviewed by A. Poortinga and C. Riano. C. Riano provided the necessary resources for policy implications. R. Chea provided the tool and guidance for social component analysis. V. Teck collected and analyzed the social data. V. Teck and R. M. B. Legaspi led the writing of the manuscript, with editorial contributions from all the other co-authors. V. Teck, R. Chea and V. Ann revised, and edited the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

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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