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Multi-Scenario Simulations of Future Forest Cover Changes Influenced by Socio-Economic Development: A Case Study in the Chiang Mai-Lamphun Basin

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Abstract

Changes in land cover in the Chiang Mai-Lamphun basin have been influenced by pressures of rapid socio-economic developments. The Markov-cellular automata and a multi-layer perceptron technique (Markov-CA-MLP) were employed to simulate three scenarios in 2021. Then, the future land cover maps in 2030 and 2050 were built based on the transition probability metric from 2021. The different scenarios were based on socio-economic schemes, which include the business-as-usual (BaU), the ecological protection scenario (EPS), and the baseline development scenario (BDS). A result of model validations using 534 ground survey points in 2021 showed that the BaU model in 2021 generated the highest overall accuracy (82.77%) with a Kappa value of 0.7846, quantity disagreement value of 0.0693, and allocation disagreement value of 0.1030. The projected BaU in 2050 revealed a decrease in forest land (6.70%). At the same time, the built-up and agricultural areas gained 5.57% and 0.88%, respectively. In BaU, class transformation between 2021 and 2050, including forests to agricultural areas (6.04%), agricultural areas to built-up areas (4.62%), and forests to built-up areas (1.59%). The BDS depicted the lowest accuracy level compared to BaU and EPS. Following this procedure, this study can provide scientific trends for possible land use management in the Chiang Mai-Lamphun basin based on the described socio-economic settings.

Keywords: Land cover change; Multi-scenario modeling; Socio-economic driver; Markov-CA-MLP; Chiang Mai-Lamphun basin

1. Introduction

Changes in land cover and its consequences are most apparent when accompanied by significant transformations of the global surface caused by increasing population, socio-economic growth, and land management change (Landry & Ramankutty, 2015). Since 1984, the achievement of Thailand's national development strategy following the economic boom has regulated the provision of public infrastructures to serve socio-economic growth in regional centers, which directly influenced rapid urbanization in the Chiang Mai-Lamphun basin (McGrath *et al.,* 2017). Recent studies entitled improvements of road infrastructure, especially in remote areas, accelerated disturbance in forest biome and converted to agricultural or residential areas (Sangawongse *et al.,* 2012; McGrath *et al.,* 2017; Lee *et al.,* 2022). Indeed, geospatial analysis based on datasets published by Land Development Department (2020) showed that the remaining forest cover decreased between 2008 and 2018 from 62.78% to 61.64% of the total area

(9,524.98 km^2). Besides the area conversion, changes in the spatial pattern of forest areas in the Chiang Mai-Lamphun basin were directly related to the deterioration of ecosystems as it could reduce the forest's capacity to supply ecosystem services (Arunyawat & Shrestha, 2016; Elliott *et al.,* 2019).

Under Thailand's forest conservation policies, the Chiang Mai-Lamphun basin is managed to resist the drivers of change, varying from the lower basin to the upland forests (McGrath *et al.,* 2017). Most upland forests are managed under protected area legislation, ranging from the most stringent to community-managed forests (Pomoim *et al.,* 2021). On the other hand, comprehensive land use plans were imposed in the lower basin, described as built-up areas surrounded by agricultural wedges and satellite cities (Department of Public Works and Town & Country Planning, 2019; McGrath *et al.,* 2017). Although protected area network and land use policy were enforced to sustain the forest ecosystem in this region, their efficacy has been both commended and criticized because some parts were designed primarily on economic potential, which caused conflict with stakeholders (Elliott *et al.,* 2019; Singh *et al.,* 2021).

The multi-simulation of land cover scenarios demonstrated an understanding of the drivers and trends of future forest changes as a way to improve the diagnosis of key success and the formulation of strategies for developing policy and legislation (International Union for Conservation of Nature & World Resources Institute, 2014; Mayer *et al.,* 2016). The Markov-CA-MLP technique may be utilized to evaluate the significance of land transformations from historical data, compute transition potential models using driving variables, and predict future land cover maps under contrary scenarios (Hamad *et al.,* 2018; Kamusoko *et al.,* 2011; Shen *et al.,* 2020).

This article aimed to use data from the Chiang Mai-Lamphun basin as a case study to analyze the likely effects of various socio-economic conditions on land cover change in the region, with the combined use of multi-scenario simulations. The objectives were (1) to simulate multiple land cover scenarios in 2021, 2030, and 2050 using the Markov-CA-MLP, (2) to validate land cover model accuracy in 2021 using field surveys, and (3) to address characteristics and trends using landscape-level indices. The study outcomes are expected to lead policymakers to improve integration strategies in the research area.

2. Materials and Methods

2.1 Study Area

The Chiang Mai-Lamphun basin was chosen as a case study because of its high possibility of land transformation influenced by rapid socio-economic development (McGrath *et al.,* 2017). The study area is located from 18°30'N to 19°N and from 98°45'E to 99°15'E. It is kidney-shaped with mountain ranges on either side, which reach a maximum elevation of 1,685 m to the west and 1,025 m to the east (Margane & Tattong, 1999). The width of this basin reaches more than 25 km, whereas the lower basin is the location of the central business districts of Chiang Mai and Lamphun provinces (McGrath *et al.,* 2017). The boundary of the study area was defined by using the hydrology toolset and watershed model in ArcGIS Pro (version 10.4). It encloses approximately 9,524.98 km^2. The boundary of the study area is illustrated in Figure 1.

2.2 Data Source and Preprocessing

Datasets of land cover in the Chiang Mai-Lamphun basin from 2008 to 2018 were derived in shapefile format with the 1:25,000 scale map, which was developed from ortho-aerial photographs at 0.75 m resolution, field investigation, and satellite imagery from THEOS (2 m resolution after pan sharpening), Landsat 8 OLI (30 m resolution), and Sentinel-2 (10 m resolution) (Division of Land Use Planning and Policy, 2020; Land Development Department, 2020). The land cover datasets were projected onto WGS 84 UTM zone 47 datum and rasterized to 30 m resolution. Then, the land cover datasets were reclassified into five classes following Thailand's level 1 land use class (Anderson *et al.,* 1976; Klindao, 2007). The datasets, ancillary data, and their sources are denoted in Table 1.

The land cover classes and their definitions are explained as follows:

Forests: land areas dominated by the tree (deciduous forest, evergreen forest, agroforestry, and plantation forest).

Agricultural areas: lands used for systematic and controlled rearing, plantation, and livestock for human food production (paddy field, crops, perennials, orchards, horticulture, pastures, aquatic plants, shifting-swidden cultivation, farmland, and aquacultural land).

Built-up areas: urban areas and infrastructures (city, commercial and service, village, transportation and communication, industrial, and institutional land).

Miscellaneous areas: other land covers without buildings, agricultural activity, or forest vegetation (rangeland, wetland, garbage dumps, mines, and pits).

Water bodies: surface water (natural and artificial water bodies).

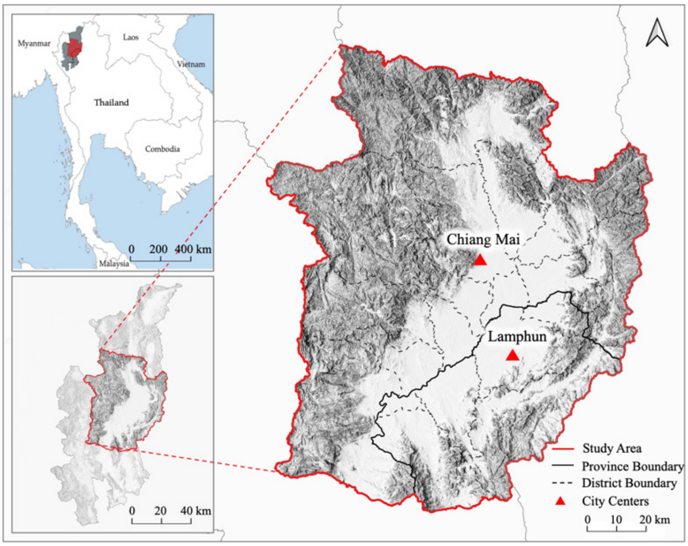

Figure 1. Location and boundary of the study site. The topographic map was adopted from Environmental Systems Research Institute (2021)

Table 1. Types, formats, and sources of data used in this study.

Dataset Types	Years	Formats	References
Land cover data	2008-2018	Shapefile	Land Development Department (2020)
Chiang Mai comprehensive-land use plan (2013) and Lamphun comprehensive Land use plan (2017)	2013 and 2017	Shapefile	Department of Public Works and Town & Country Planning (2019)
National reserved forest	2020	Shapefile	Royal Forest Department (2020)
National parks, Non-hunting areas, and Wildlife sanctuary	2020	Shapefile	Department of National Parks Wildlife and Plant Conservation (2020)
Thailand administrative boundaries	2019	Shapefile	United Nations Office for the Coordination of Humanitarian Affairs (2019)
Road network	2020	Shapefile	OpenStreetMap contributors (2020)
Digital elevation model (DEM)	2019	ASCII	NASA *et al.* (2019)
Population density	2020	Tabulated data	Department of Provincial Administration (2020)

Note: datasets converted to a raster at 30 m resolution.

Scenario's Assumption and Driving Variables
- Business as Usual Scenario: current socio-economic trends with land use policy intervention
- Ecological Protection Scenario: strict land use policy intervention
- Baseline Development Scenario: no land use policy intervention

Multi-Scenario Simulations
- Calibration: change detection in 2015 and 2018, Multi-Layer Perceptron, and Markov-Cellular Automata using Land Change Modeler in TerrSet 2020
- Results: multi-scenarios map in 2021, 2030, and 2050

Model Accuracy Validation
- Ground survey (534 points): class equalized stratified random in 2021
- Accuracy metrics: overall accuracy, Kappa, quantity disagreement, and allocation disagreement

Change Characteristics
- Landscape change analysis: CROSSTAB module in TerrSet 2020
- Landscape indices: FRAGSTATS

Figure 2. Conceptual framework of the study

2.3 Multi-scenario simulation

Multi-scenario simulation is a method that analyzes current land cover change processes and forecasts future development in an alternative context (Mayer *et al.,* 2016). Socio-economic variables were utilized as a factor of land cover change and deforestation (Samie *et al.,* 2017). Variable usages and treatment procedures are shown in Table 2, following the TerrSet manual (Eastman, 2020). The chosen variables were converted to IDRISI format with 30 m pixels. Fuzzy operations were used for making distance variables (i.e., logistic variables) to construct the forecast based on a continuous scale of suitability (Amato *et al.,* 2018). For example, an agricultural area located in a built-up neighborhood has a higher chance of becoming urbanized (Amato *et al.,* 2018; Eastman, 2020). For zoning constraint-incentive, strictness of land use enforcement values were assigned in IDRISI raster using reclassification tool, ranged from the maximum constraint (value = 0), constraint (0 < value < 1), no constraint (value = 1), and incentive (value > 1) (Eastman, 2020). The protocols were set for the following three scenarios:

The Business-as-Usual Scenario (BaU) is based on recent trends in socio-economic development and land use enforcement (Kamusoko *et al.,* 2011). Further, various levels of law enforcement have been collated from studies on the effectiveness of protected areas and comprehensive land use plans (Department of Public Works and Town & Country Planning, 2019; Pomoim *et al.,* 2021; Singh *et al.,* 2021).

Ecological Protection Scenario (EPS) emphasizes socio-economic development based on ecological protection by using strict forest enforcement and all level protected areas (Chen *et al.,* 2021; Kamusoko *et al.,* 2011). Therefore, the EPS can depict the gap between existing and ideal ecological management (Chen *et al.,* 2021).

Baseline Development Scenario (BDS) follows the socio-economic development without land use enforcement (Chen *et al.,* 2021).

Future forest changes under different land cover scenarios were projected by Markov-CA-MLP in TerrSet 2020: Land Change Modeler (Denis & Sorin, 2019; Eastman, 2020; Marinelli & Bernetti, 2020; Mishra *et al.,* 2014). The processing flow in Land Change Modeler is shown in Figure 3. The transition probability metric based on transition potentials in EPS was modified to constrain forest loss (Kamusoko *et al.,* 2011). Finally, the scenario maps were generated for the years 2021, 2030, and 2050 based on the present state of the transition probability for each transition (Eastman, 2020; Shade & Kremer, 2019).

Table 2. Data treatments and variables were used for BaU, EPS, and BDS

Input Data	Data Treatments	BaU	EPS	BDS
Digital elevation model (DEM)	Fill	*1,2,3,5,6*	*1,2,3,5,6*	*1,2,3,5,6*
Distance from slope	Slope, fuzzy (sigmodal)	*1,3,4*	*1,3,4*	*1,3,4*
Distance from city center	Cost distance, fuzzy (sigmodal)	*2,3,4,6*	*2,3,4,6*	*2,3,4,6*
Distance from the built-up area	Fuzzy (linear)	*1,3,4,6*	*1,3,4,6*	*1,3,4,6*
Distance from miscellaneous area	Fuzzy (linear)	*1,3,4*	*1,3,4*	*1,3,4*
Distance from the agricultural area	Fuzzy (linear)	*1,3,4*	*1,3,4*	*1,3,4*
Population density	Standard deviation (stretch)	*2,3,4,6*	*2,3,4,6*	*2,3,4,6*
Distance from road	Fuzzy (j-shaped)	*1,3,4,5*	*1,3,4,5*	*1,3,4,5*
Comprehensive land use plan	Constrain, incentive	*3,5*	*3,5*	*N/A*
National reserved forest, National parks, Non-hunting areas, and Wildlife sanctuary	Constrain	*3,4*	*3,4*	*N/A*
Transition potential map	Transition probability metric modification	*N/A*	*3,4*	*N/A*

Note: *N/A* refers to not applicable
[1]Amato *et al.* (2018), [2]Chen *et al.* (2021), [3]Eastman (2020), [4]Kamusoko *et al.* (2011),
[5]Marinelli and Bernetti (2020), [6]Samie *et al.* (2017)

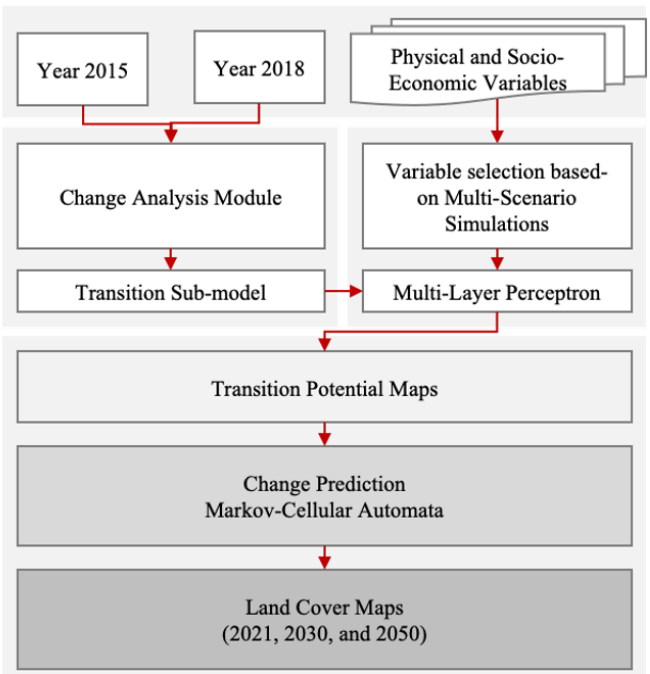

Figure 3. The processing procedure of multi-scenario simulation using Land Change Modeler

2.4 Accuracy Validation

The accuracy metrics were examined to verify map quality in 2021 by measuring the agreement between the produced maps and the reference data (Shao *et al.,* 2019). The sample size was determined based on multinomial distribution to reach an appropriate number that validity represented the map accuracy (Congalton & Green, 2009). The calculation of the sample numbers is as follows:

$$n = B \times \prod(1 - \prod)/b^2 \qquad (1)$$

where n represents the appropriate sample numbers, b represents the desired precision of the sample, B is a critical value that determine from the Chi-square table with 1 degree of freedom and left-tail p-values = $1- \propto /k$, k represents numbers of land cover class where $\propto$ values represent the probability of making wrong decisions, which is directly related to the confidence level ($\propto = 1-$ confidence level), $\prod$ represents the class proportion presented on the map, $\prod$ was assumed as 30% in normal condition.

In this study, 550 sample numbers were calculated from Equation 1, with five categories in our classification scheme (k = 5), that the desired confidence level is 95%, and the desired precision is 5%. The sampling points were assigned for the field survey based on the road buffer in 2021 predicted maps using equalized class-stratified random in ArcGIS Pro (version 10.4) (Environmental Systems Research Institute, 2022; OpenStreetMap contributors, 2020). A 50 m buffer from the roadside was used for stratification that facilitates accessibility during fieldwork (Haub *et al.,* 2015). Despite the calculated sample numbers, only 534 ground truths were derived from May 2021 and used for validation of the scenarios of 2021, including forests (109 points), agricultural areas (106 points), miscellaneous areas (106 points), built-up areas (107 points), and water bodies (106 points). All accuracy indicators were calculated using Map Tools (Salk *et al.,* 2018) based on confusion metrics on a per-map basis (all categories) and a per-class basis (binary maps) as follows:

Overall accuracy was used to explain the proportion of pixels correctly classified in the predicted maps (Ayala-Izurieta *et al.,* 2017; Shao *et al.,* 2019). The overall accuracy was computed as:

$$\text{Overall accuracy} = \frac{\sum_{j=1}^{q} n_{jj}}{\sum_{i=1}^{q} n_{i+}} \qquad (2)$$

where q represents the number of categories, the predicted categories (i = 1, 2, ..., q) are represented by rows, the references ($j = 1, 2, \ldots, q$) are represented by columns, n_{jj} represents the number of pixels categorized as belonging to class i and belonging to category j in the reference dataset, n_{i+} represents the total number of pixels categorized as belonging to class i in the map.

Kappa was used to measure the chance agreement between the predicted map and the reference data (Salk *et al.,* 2018). The statistical testing of Kappa was accounted to compare accuracy to a baseline of randomness (Pontius & Millones, 2011). Kappa was computed as:

$$\text{Kappa} = \frac{\sum_{i=1}^{q} n_{ii} - \sum_{i=1}^{q}(n_{i+} \cdot n_{+i})}{N^2 - \sum_{i=1}^{q}(n_{i+} \cdot n_{+i})} \qquad (3)$$

where q represents the number of categories, the predicted categories (i = 1, 2, ..., q) are represented by rows, the reference (j = 1, 2, …, q) are represented by columns, n_{ii} represents the number of observations in row i and column i, n_{i+} and n_{+i} represents the total number of observations in row i and the total number of observations in column i, respectively, and N represents the number of observed pixels in the confusion metric.

Quantity disagreement measured the difference between the predicted map and reference data due to the less than perfect match in the proportions of the class categories (Ayala-Izurieta *et al.,* 2017; Salk *et al.,* 2018) The definition of quantity disagreement was proposed by Pontius & Millones (2011). The quantity disagreement of each land cover class i was computed as:

$$\text{Quantity disagreement} = |p_{i+} - p_{+i}| \quad (4)$$

where p_{i+} represents the estimated proportion of land cover class in the predicted categories, p_{+i} represents the estimated proportion of land cover class in the reference categories.

Allocation disagreement was used to interpret errors due to differences in the location of map categories (Pickard *et al.,* 2017; Salk *et al.,* 2018). This accuracy metric provides an estimate of how well each model simulates pixels spatially, with some allocations having greater similarities to the observed land cover than others (Pontius & Millones, 2011). The allocation disagreement of land cover class *i* was computed as:

$$\text{Allocation disagreement} = 2\min(p_{i+} - p_{ii}, p_{+i} - p_{ii}) \quad (5)$$

where the first argument (p_{i+} - p_{ii}) within the minimum function represents the omission of the predict categories, the second argument (p_{+i} - p_{ii}) represents the commission of the reference categories, p_{i+} represents the estimated proportion of land cover class in the predicted categories, p_{+i} represents the estimated proportion of land cover class in the reference categories, p_{ii} represents the proportion of the pixels that are correctly predicted.

2.5 Change Characteristics

Landscape change analysis was used to detect quantitative changes in predicted maps (Fichera *et al.,* 2017). The CROSSTAB in TerrSet calculates changes in the predicted maps in BaU, EPS, and BDS (Eastman, 2020). Both the class percentages and shifting quantity were interpreted in the Sankey diagram at the interval changes in two periods (2021:2030 and 2030:2050).

The landscape-level metrics were used to examine land characteristics on a macro-scale (Narmada *et al.,* 2021; Sertel *et al.,* 2018). Changes in spatial characteristics were detected using FRAGSTATS (version 4.2) (McGarigal, 2015). The predicted maps were exported as 4-bit unsigned GeoTIFF to meet software compatibility (McGarigal, 2015). Landscape-level metric types used in this study are shown in Table 3.

3. Results and Discussion

3.1 Predicted Scenarios and Accuracy Validation

Predicted scenarios using Markov-CA-MLP showed the trends forecast of land cover maps in 2021, 2030, and 2050 resulting from the BaU, EPS, and BDS scenarios (Figure 4). Accuracy validation was used to ascertain the quality of the predicted map in 2030 and 2050 based on the comparison of predicted scenarios for 2021 and the actual ground truth in 2021 (Hamad *et al.,* 2018; Shade & Kremer, 2019). The accuracy results in 2021 of each scenario showed that BaU had the highest overall accuracy (82.77%), followed by EPS (82.58%) and BDS (72.85%) (Figure 4). The accuracy in class-level for forests, built-up areas, and water bodies was higher

Table 3. Landscape-level metrics, abbreviations, and descriptions (Aguilera *et al.,* 2011; McGarigal, 2015; Sertel *et al.,* 2018)

Indices	Descriptions
Mean shape index (SHAPE_MN)	SHAPE_MN describes the ratio between the actual perimeter of the patch and the hypothetical minimum perimeter of the patch weighted by patch area. The minimum perimeter equals the perimeter if the patch would be maximally compact.
Aggregation index (AI)	AI is the number of like adjacencies divided by the theoretical maximum possible number of like adjacencies for that class summed over each class for the entire landscape.
Shannon's diversity index (SHDI)	SHDI is a widely used metric in ecology that takes both the number of classes and the abundance of each class into account.
Simpson's diversity index (SIDI)	SIDI is less sensitive to rare class types than SHDI. It can be interpreted as the probability that two randomly selected cells belong to the same class.

than in agricultural areas and miscellaneous areas (Figure 5A). The high accuracy for the forests and built-up areas classes showed the suitability for transition potential modeling (Figure 5). In comparison, the low accuracy of agricultural classes and miscellaneous classes (Figure 5A-D) was probably resulted from the lower capabilities of model calibration. The Kappa showed similar trends to the overall accuracy in which the result of BaU, EPS, and BDS were 0.7846, 0.7823, and 0.6522, respectively (Figure 5). The highest accuracy and Kappa for water bodies in every scenario over the study period may result from no transition simulated for water bodies (Figure 4; Figure 5), as the hydrological factor was not concerned as a socio-economic factor (Choudhari, 2013). In the future, additional bio-physical data that correspond to land use decisions following the study carried out by Choudhari (2013) should be incorporated into the modeling framework to improve the model's credibility, especially rainfall and drainage maps.

The quantity disagreement describes an opposite pattern to overall accuracy and Kappa. BDS had the highest quantity disagreement, followed by EPS and BaU, respectively (Figure 4). At the class level, agricultural areas had the highest quantity disagreement, followed by miscellaneous areas in all scenarios (Figure 5C). At the same time, the quantity of disagreement of forests class in BDS was distinctly higher than in BaU and EPS (Figure 5C). Besides, the agriculture and miscellaneous classes had the highest allocation disagreement, followed by the built-up class (Figure 5D). In contrast, forests showed the lower allocation disagreement (Figure 5D). However, water bodies showed the lowest quantity and allocation disagreement caused by no change predicted in this class (Figure 5C; Figure 5D).

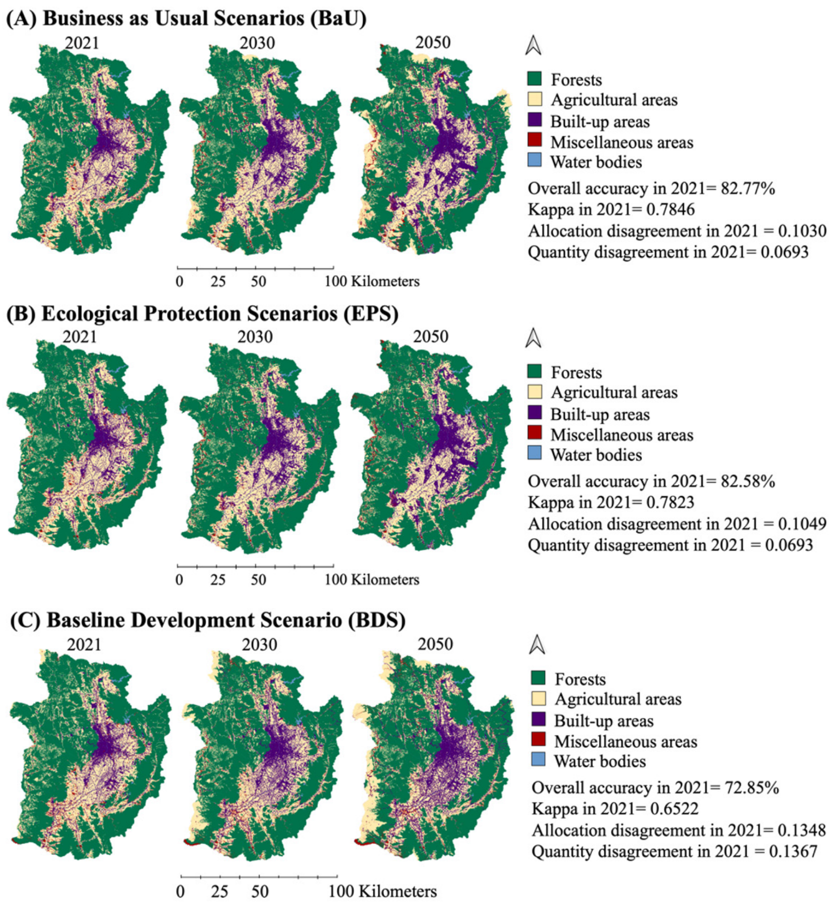

Figure 4. Predicted land cover maps in 2021, 2030, and 2050 for the scenarios: (A) BaU, (B) EPS, and (C) BDS

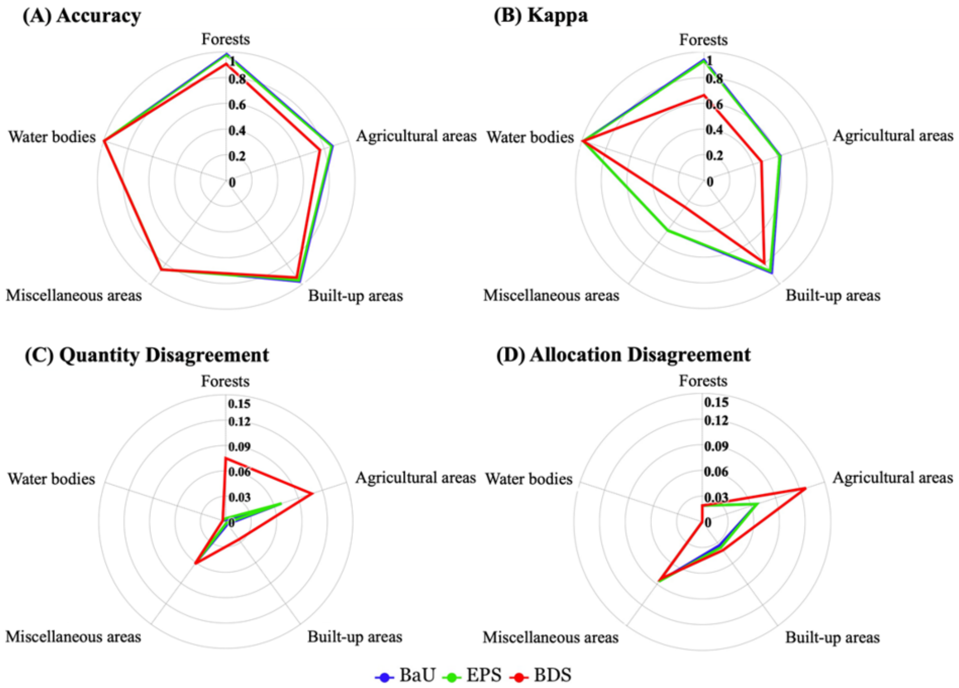

Figure 5. Class-level accuracy metrics calculated on confusion metrics derived from simulated maps in 2021: (A) Accuracy, (B) Kappa, (C) Quantity disagreement, and (D) Allocation disagreement. The percentage of accuracy is expressed as decimals

3.2 Landscape Changes and Characteristics

Figure 6 shows the land cover proportion derived from BaU, EPS, and BDS. For the most part, the built-up areas had increased, while the areas for water bodies remained at 1.21% over the study periods. However, the results for the agricultural areas and forest classes displayed different trends. In BaU, forest covers are predicted to decrease over the study periods, while agricultural areas and miscellaneous areas are increased (Figure 6A). In BDS, the class proportions were like BaU (Figure 6C). However, the deforestation caused by the expansion of built-up areas in BaU was 0.09% greater than that found in BDS between 2021 and 2030, while the deforestation by agricultural expansion was identical (2.00%) (Figure 6A; Figure 6C). The amount of forest areas changed to miscellaneous areas between 2021 and 2030 of BaU was less than 0.09% compared to BDS (Figure 6A; Figure 6C). Reductions in forest areas contributed to built-up area expansion in BaU, which was 0.32% greater than BDS between 2021 and 2030 (Figure 6A; Figure 6D). Between 2030 and 2050, the deforestation contributed by agriculture in BaU rose by 1.26% compared to the previous period, and 0.05% less than showed in BDS (Figure 6A; Figure 6D). The amount of forest areas turned to miscellaneous areas in BaU was 0.28% less than in BDS (Figure 6A; Figure 6C).

In EPS, the proportion of forests and water bodies was predicted to remain at 61.65% and 1.21%, respectively. In addition, in BaU and BDS, the rise in built-up areas and the decrease in agricultural regions are distinct (Figure 6B). A major contribution to the decrease of agricultural areas was an expansion of built-up areas and conversion to miscellaneous areas (Figure 6B). In comparison, the predicted forest change in BaU and BDS was 2.36% greater than forest change in EPS between 2021 and 2030, and 4.34% between 2030 and 2050 (Figures 6A-C). The increase of built-up areas, agricultural areas, and agriculture areas in EPS was not contributed by forest reduction as in BaU and BDS (Figures 6A-C).

Landscape-level metrics depicted the changes in spatial patterns of simulated land cover maps of three predicted scenarios (Figure 7). The decreasing trend of the mean shape index in Figure 7A revealed the transformation from irregular shapes of natural land cover to basic geometric shapes of manmade land use (Aguilera *et al.,* 2011), while the decreasing trend of the aggregation index in Figure 7B reflected the increase of patch isolation in the subsequent years (Fichera *et al.,* 2017). In comparison, the mean shape index and aggregation index in BaU were higher than in BDS but lower than in EPS (Figure 7A; Figure 7B). When compared the mean shape index to the data in 2021, EPS showed the smallest changes due to the preservation of forest patches (Figure 7A). Trends for Shannon's Diversity Index and Simpson's Diversity Index describe the increase of disorder and uncertainty of individual land classes, and the relative abundance of each class in the landscape, respectively (McGarigal, 2015).

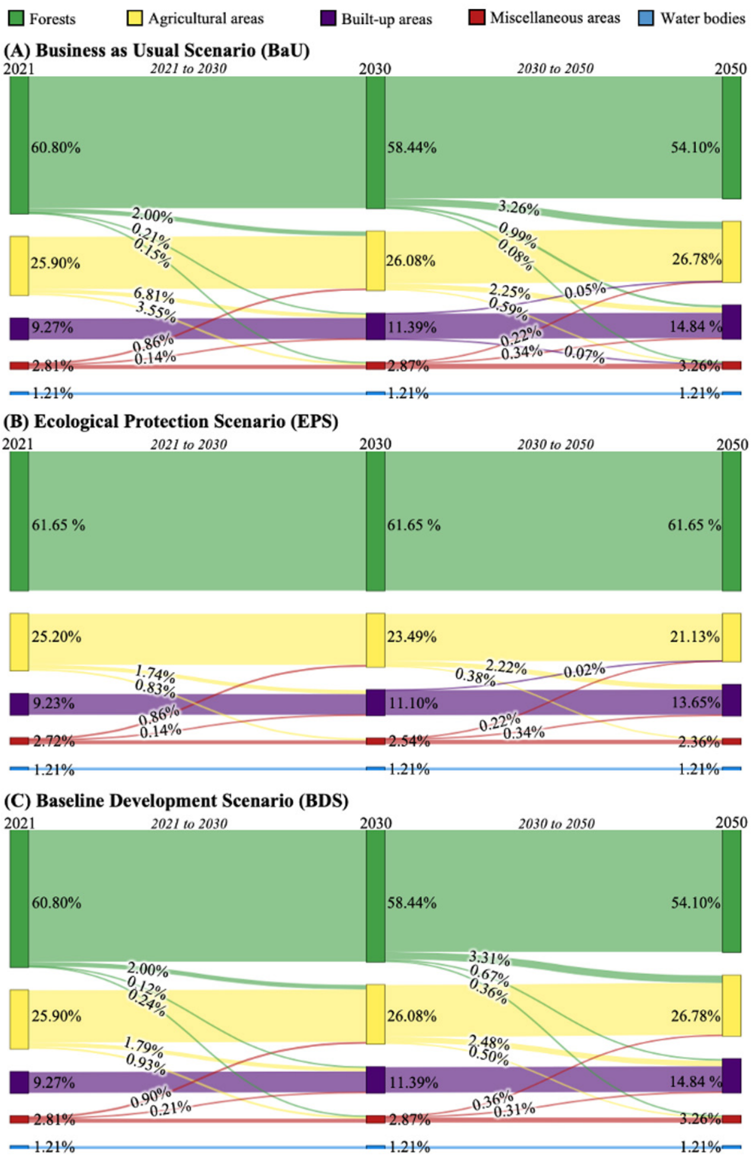

Figure 6. Relationships between land cover classes derived from landscape change analysis. The results were interpreted by land cover scenarios in 2021, 2030, and 2050: (A) BaU, (B) EPS, and (C) BDS

Alternatively, the EPS forecasts the development under forest management guided explicitly by ecological values (Xi *et al.,* 2010). Aside from preserving forest covers in EPS, the built-up areas replaced the existing agricultural and miscellaneous areas due to the limited available space for land utilization (Figure 6B). The trade-offs found in EPS showed that the Chiang Mai-Lamphun basin would face a shortage of cultivable land (Figure 6B). Therefore, the socio-economic development under EPS may involve an innovative solution to maximize the agricultural production within the remaining areas instead of converting forest areas (Mayer *et al.,* 2016). On the other hand, the most aggregated pattern shown in BDS was driven by the development in the absence of land use policy interventions (Figure 7B), despite geographical features playing a role as natural buffers to safeguard natural habitats. The evidence of increased patch fragmentation and interpretation based on Fichera *et al.* (2017) highlighted the significance of protected area networks and their enforcement to preserve the quality of forest habitats.

3.3 Trends, Conflicts, and Future Resolutions

Although forests in the Chiang Mai-Lamphun basin are primarily administered by a protected area network, areas vulnerable to destruction still exist (Elliott *et al.,* 2018; Elliott *et al.,* 2019; Lee *et al.,* 2022). The national reserved forest in Thailand is less effective in the prevention of forest loss compared to the national parks system (Pomoim *et al.,* 2021; Singh *et al.,* 2021). Conflicted stakeholders and agricultural land redistribution may jeopardize their protected area potential, particularly in the national reserved forest (Singh *et al.,* 2021). The 4th revision of Chiang Mai's comprehensive land use plan in 2022 highlighted government-initiated land redistribution for agricultural activities in semi-protected regions, particularly in the San Sai, Mae Taeng, and Mae Rim districts in Chiang Mai (Department of Public Works and Town & Country Planning, 2022). In terms of policy implementation, Chiang Mai and Lamphun provinces still have rooms for improvement, especially the goals for local forest conservation.

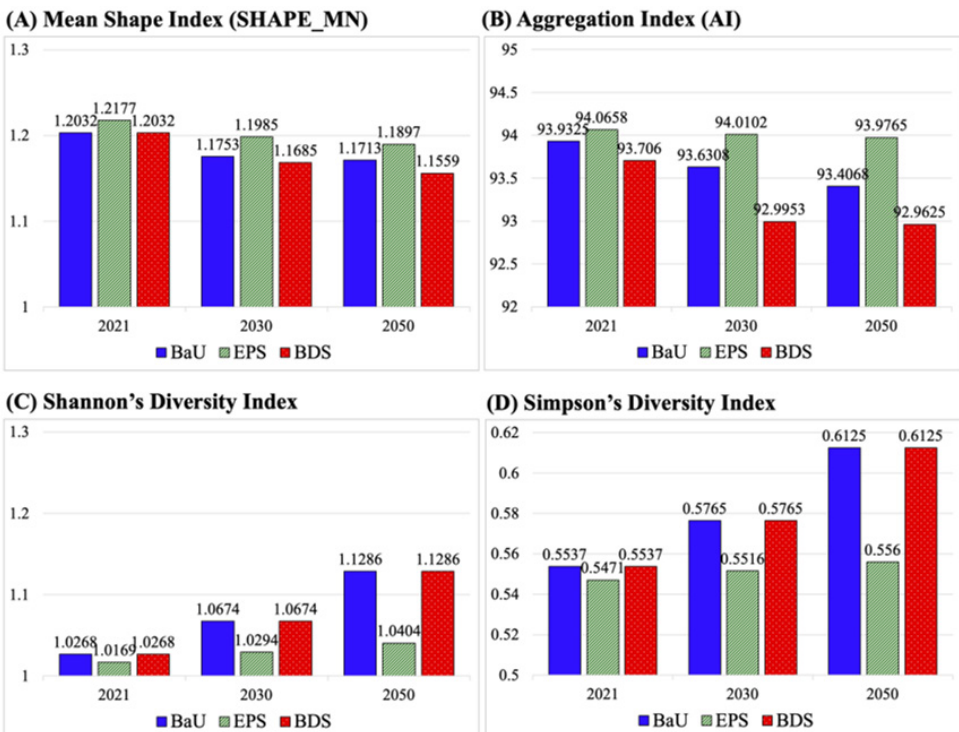

Figure 7. Landscape-level metrics: (A) Mean shape index, (B) Aggregation index, (C) Shannon's diversity index, and (D) Simpson's diversity index

Despite our findings, BaU is the best scenario for the Chiang Mai-Lamphun basin to understand existing and future socio-economic forces. The future developments are suggested to be more concerned with ecological values than exploiting the vulnerabilities of protected regions. Additionally, forest conservation should focus on both the socio-economic factors and the selection of priority regions by engaging all stakeholders.

4. Conclusion

Different perspectives show future forest changes driven by socio-economic development in the Chiang Mai-Lamphun basin. This article proposes the use of Markov-CA-MLP model in Land Change Modeler for simulation of future land cover maps. Three development scenarios (BaU, EPS, and BDS) for the years 2021, 2030, and 2050, were designed according to different socio-economic variables. The accuracy test in 2021 demonstrated that the BaU could better fit the study site development's pathway. If factors in BaU persist, future forest lands will experience pressure from the development incorporated by the existing land use regulations. On the other hand, the EPS projected good practices of forest area protection, and the BDS predicted land cover changes without controls. These findings are anticipated to support the requirement for sustainable development, where ecological values need to be concerned in tandem with future socio-economic growth.

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