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Scenario-Based Land Cover and Land Use Change Modeling in Mae Chang Watershed, Lampang Province, Thailand

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ABSTRACT

The Mae Chang watershed is part of the headwaters of the Wang River, located in Lampang Province in Northern Thailand. Resource pressures at forest-agriculture-extractive frontiers make this landscape crucial for studying land-habitat conversion and guiding sustainable land-use planning. Thus, this study interpreted LULC (1989, 2005, 2013, 2021) and projected LULC for 2029 and 2037 under BAU, conservation (CON), and development (DEV) scenarios using TerrSet's LCM-MLP with local drivers, isolating intervention effects by contrasting CON/DEV (with constraint and incentive (CI) layers) against BAU (no CI). From 1989 to 2021, deciduous forest declined 23.3% (-249.01 km²), from 1,070.41 to 821.40 km² (65.40→50.18% of the watershed; -15.2 percentage points), while field crops increased by 104.7%, perennial crops by 97.3%, mines/pits by 240.8%, and urban areas by 28.8% based on human activity. Sub-model accuracies ranged 53-92%, and validation achieved Kstandard 0.824, Kno 0.861, Klocation 0.893, exceeding the success threshold. The three future scenarios yielded similar projected areas in both 2029 and 2037 but there were location differences. The deciduous forest area in 2029 and 2037 declined by 22.3% and 31.5%, respectively for all scenarios compared with 2021. The CON scenario outperformed BAU/DEV because strict no-conversion constraints in protected forests and restricted area effectively prevent ongoing deforestation, offering a practical simulation-based tool to support and implement land-use policies at local and regional scales. These findings provide a validated, transferable framework that isolates policy effects and supports evidence-based land-use planning in tropical headwatersheds.

HIGHLIGHTS

- Headwatershed-specific LCM-MLP integrates local drivers and Constraint/Incentive (CI) layers.
- Deciduous forest fell 23.3% (-249 km²) from 1989 to 2021, while evergreen forest remained stable.
- Concerningly, deciduous forests decline while agriculture expands across all future scenarios.
- CON outperformed BAU/DEV via no-conversion constraints in protected areas.
- The model offers a practical tool for land-use policy implementation.

1. INTRODUCTION

Land use and land cover (LULC) change (LULCC) is a key factor driving global biodiversity loss and influencing processes that impact ecosystem services (Tscharntke et al., 2012). Direct and indirect human activities have triggered processes leading to land degradation, impacting the ecological integrity of affected areas (IPCC, 2019). Since 1970, this situation has caused the greatest negative effects on both terrestrial and freshwater ecosystems (IPBES, 2019), with LULCC affecting almost 32% of the global land area between 1960 and 2019 (Winkler et al., 2021).

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Extensive changes in land conditions are expected to continue due to ongoing land use changes, leading to substantial declines in net primary productivity, reductions in soil carbon levels, and losses of biodiversity (Van der Esch et al., 2017). Quantifying LULCC is therefore essential to address environmental challenges (Winkler et al., 2021). In Southeast Asia, a global biodiversity hotspot, LULCC drivers such as deforestation, increased agricultural intensification, urbanization, mining activity, dam construction, and wetland reduction are already threatening ecosystems (Hughes, 2017), and these losses are projected to persist through to 2050 (Van der Esch et al., 2017). Thailand is one of countries in the region most affected by land conversion (Hughes, 2017) and has experienced rapid economic growth since the 1980s, primarily fueled by agriculture for export (Wang et al., 2022). While this development has been concentrated in urban centers and lowland regions, it has also extended into mountainous areas (Schreinemachers et al., 2013), particularly in Northern Thailand.

According to the Land Development Department of Thailand (LDD) (2023), the forest area in Northern Thailand decreased by 9.66%, from 57.69% to 52.12%, between 2006/2007 and 2019/2021, respectively, while the agricultural area increased by 16.94%, from 34.65% to 40.52%, during the same period, especially in perennial and field crops. The five northern provinces with the greatest relative forest reduction from 2007 to 2018 are Chiang Rai (-19.51%), Nan (-16.03%), Phayao (-8.83%), Lampang (-8.81%), and Phrae (-6.94%). Nevertheless, in northern Thailand, protected areas (PAs) managed by the Department of National Parks Wildlife and Plant Conservation (DNP) more effectively controlled deforestation than in non-protected areas (Lee et al., 2022; Liu et al., 2022), while national reserved forest which is located adjacent and outside PAs, operated by Royal Forest Department (RFD), tend to be severely encroached.

Therefore, to address environmental problems related to LULCC, future LULC should be projected in terms of location and quantity using scenario-based models such as CA, CLUE-S, MCDA, LCM, FLUS, and agent-based models (Alcamo et al., 2006; Gomes et al., 2021).

The Land Change Modeler (LCM) is a tool used to simulate future land use and land cover (LULC) based on past changes. It employs various methods, e.g., the Multi-Layer Perceptron (MLP) Neural Network (NN), Logistic Regression (LR), and SimWeight (SW) (Eastman and Toledano, 2018). The most favorable method is MLP-NN Markov Chain (MC) or MLP-MC due to its effectiveness (Aghababaei et al., 2024; Entahabu et al., 2023) and higher accuracy (Dey et al., 2021; Mishra et al., 2018). Studies in Thailand have also applied the LCM model for prediction. Several studies focused on general simulations or comparative analyses based on historical land use changes and key driving factors, distributed across all regions of the country, both through administrative boundaries and watershed scales (Paiboonvorachat and Oyana, 2011; Suwanlertcharoen et al., 2013; Losiri et al., 2016; Ongsomwang and Boonchoo, 2016; Chuankamnerdkarn, 2020; Hormwichian et al., 2023; Iamchuen et al., 2023; Phonphan et al., 2024). For the northern Thailand context, a study in the Chiang Mai-Lamphun Basin demonstrated the land use projection model’s potential for integrating constraint and incentive (CI) factors to produce realistic scenarios, simulating three future scenarios for 2030 and 2050—the business-as-usual (BaU), the ecological protection scenario (EPS), and the baseline development scenario (BDS)—using LCM Markov-CA-MLP (Arunsurat et al., 2023). The results showed that, under strict constraints, the EPS could maintain forest cover at 61.65% in 2021, 2030, and 2050.

The Mae Chang Watershed is located in Lampang Province, Northern Thailand. The watershed is a tributary catchment of the main watershed, Wang, the uppermost part of the Chao Phraya River Watershed. Most of the area is covered by forest, primarily protected by the Royal Forest Department (RFD) of Thailand and the Department of National Parks, Wildlife, and Plant Conservation (DNP) of Thailand (Office of the National Water Resources, 2020). In addition, there are several anthropogenic activities in this watershed, such as forest plantations managed by the Forest Industry Organization (FIO) of Thailand and agricultural areas, such as paddy fields and field crops, and there is some agriculture located in agricultural land reform areas managed by Agricultural Land Reform Office (ALRO) of Thailand. In addition, extractive activity such as coal lignite mining for electricity generation operated by the Electricity Generating Authority of Thailand (EGAT) is found in this watershed, along with some other types of mines. This highlights the importance of the socio-economic dimension of timber, food, energy and ecological aspect. Deforestation and agricultural expansion has occurred in this watershed (Office of the National Water Resources, 2020), which may continue. These activities in the watershed might act as threats, causing environmental issues related to land use practices, such as soil erosion from agricultural areas (Marine Department, 2023). Therefore, understanding the historical changes in the Mae Chang Watershed, as well as future LULUC and its scenarios through the application of geoinformatics, might lead to more effective spatial planning for decision-makers and governors. The main objectives of the present study are as follows: (1) To quantify LULC changes for the years 1989, 2005, 2013, and 2021 and (2) to predict changes for 2029 and 2037 under three scenarios—business-as-usual (BAU), conservation (CON), and development (DEV)—using GIS-based MLP-MC and incorporating CI layers for scenarios construction, which reflect the real-world situation of the Mae Chang watershed to understand past and future changes for further sustainable planning.

2. METHODOLOGY

2.1 Study area

The Mae Chang watershed is a sub-watershed of the Wang watershed, the main watershed. It is located between latitudes 17°56'3.89" N - 18°33'50.15" N and longitudes 99°22'56.57" E - 99°57'9.43" E (Figure 1) and it covers an area of 1,636.8 km² (Office of the National Water Resources, 2021). The topography of the Mae Chang watershed consists of a mountain range in the western part, followed by hills, valleys, and plains. The elevation ranges from 126 to 1,305 meters above mean sea level (MSL). The main channel is the Nam Mae Chang, which flows from the northeastern part of the watershed through the Mae Chang Reservoir and other barrages in the lower part of watershed, before merging with the Wang River at the outlet located in Koh Kha District, Lampang Province. Most of the area falls under the political boundary of Lampang Province, and mostly in Mae Moh and Mae Ta Districts.

2.2 Material

Geospatial software, including the ArcGIS platform (ArcMap and ArcGIS Pro) (ESRI, Inc., Redlands, CA), QGIS 3.22.10 (QGIS Development Team, 2022), Google Earth Pro, TerrSet (formerly IDRISI) 18.31 (Eastman, 2016), and TerrSet liberaGIS Version 20.0.0 (Eastman, 2024), were utilized to perform the LULC analysis and LULCC prediction. All geospatial data utilized was in the WGS 1984 UTM Zone 47N projected coordinate system. Rasterization was conducted and the resampling method was applied to convert the geospatial data to a 30-meter spatial resolution to harmonize it before further processing in modeling LULCC (Kimario et al., 2024; Kayitesi et al., 2024). The data used in this study is presented in Table S1.

2.3 Land use land cover (LULC) preparation and change analysis

LULC data for the years 1989, 2005, and 2021 was visually interpreted using on-screen digitization based on satellite imagery and supported information provided in Table S1. Only LULC in 2013 retrieved from LDD was directly utilized with some modification. Image interpretation elements, including tone, texture, pattern, shape, association, and site (Campbell et al., 2022), were applied during manual interpretation using the digitizing tools. The LULC nomenclature consists of 14 classes, following LDD’s system with some modifications, including: (1) Paddy Field (APAD); (2) Field Crop (AFLD); (3) Perennial (APER); (4) Orchard (AORC); (5) Other Crop (AOTH); (6) Aquaculture (AAQC); (7) Evergreen Forest (FEVG); (8) Deciduous Forest (FDCD); (9) Rangeland and Scrub (MRNS); (10) Swamp (MMSW); (11) Mine and Pit (MINE); (12) Other Miscellaneous (MOTH); (13) Urban and Built-up (URBA); and (14) Water body (WATR).

The verification points in 2021 were collected through a combination of field surveys (during early winter) and very high-resolution imagery via the Google Earth Pro platform (Raja Shekar and Mathew, 2023), using an image zoom level sufficient to distinguish land use types in accordance with the defined nomenclature and through accurate interpretation. The other truthing points were collected from aerial imagery (the main source) as well as from Google Earth Pro imagery, with the reference year selected as close as possible to coincide with the interpreted LULC for 1989 and 2005. The sample size was determined using the cumulative binomial probability distribution (Fitzpatrick-Lins, 1981), as shown in Formula 1.

$$N = \frac{Z^2pq}{E^2}, \ Z = 2 \text{ (is generalized from 1.96)} \qquad (1)$$

Where; N is the minimum sample size, Z is the Z value of 2, which is an approximation of the standard normal deviate of 1.96, corresponding to a 95% two-tailed confidence level, p is the expected percent accuracy, q = 100 − p, and E is the allowable error. In this study, more than 204 points were gathered (Ongsomwang, 2011) based on accuracy and allowable error equal to 85% and 5%, respectively.

Finally, the accuracy assessment was performed to determine the overall accuracy (Story and Congalton, 1986; Congalton and Green, 2019). The accepted accuracy value was set to 85% (Anderson et al., 1976) for the final LULC maps.

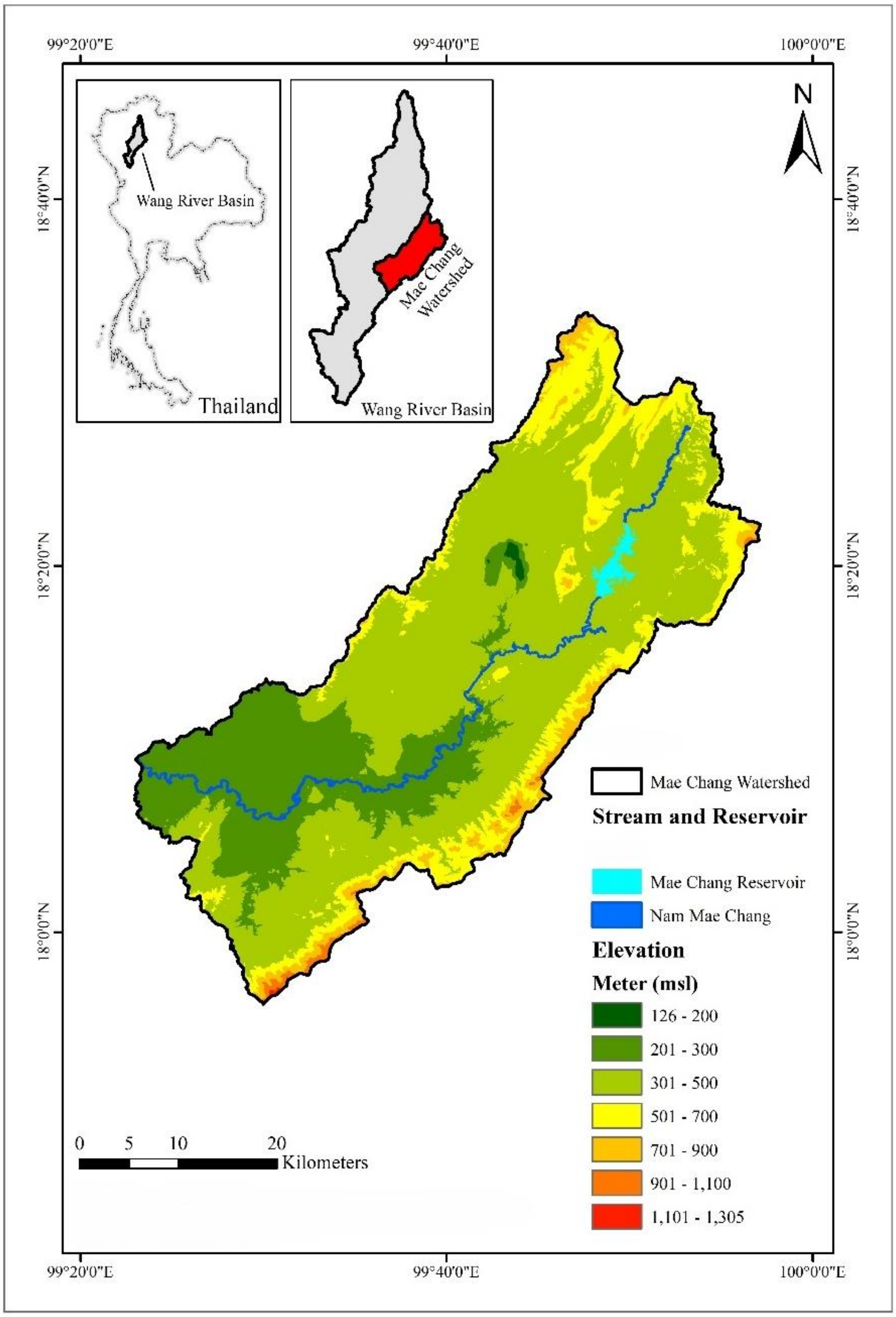

Figure 1. Mae Chang Watershed, Thailand
Data sources:
1) Thailand boundary, Royal Thai Survey Department (RTSD), OCHA HDX, ITOS, CC BY-IGO
2) River basin and watershed boundary, Office of the National Water Resources (ONWR), Thailand
3) Digital Elevation Model (DEM), Land Development Department (LDD), Thailand
4) River and reservoir, NOSTRA

2.4 Scenario construction concept

The theoretical concept and design of the scenario were based on the activation of constraint and incentive layers (Proswitz et al., 2021; Arunsurat, 2022; Gandharum et al., 2024), representing policy or intervention measures. The scenarios are divided into three alternatives as follows:

(1) Business-as-Usual (BAU): This scenario is based on historical LULCC trends without any interventions (Lin et al., 2022; Broquet et al., 2024; Saluja et al., 2024; Gandharum et al., 2024). No enforcement will be applied. No CI layers are activated (Table S2: "╳" for all layers). BAU is used as the policy-neutral baseline.

(2) Conservation (CON): This scenario is based on past LULCC trends, assuming no human activities in protected areas (Proswitz et al., 2021). This design aligns with northern Thai evidence that protected-area enforcement curbs encroachment and limits fragmentation (Lee et al., 2022). The national reserved forest areas, particularly conservation zones (Zone C), and national park will be employed. Additionally, watershed classification class 1 (WSC1), which restricts land use to preserve headwater sources (Tongdeenok, 2023), will also be applied. Operationally, these protected units are enforced as absolute constraints (CI=0) in Table S2, prohibiting land-use conversion within Zone C, National Parks, and WSC1.

(3) Development (DEV): This scenario is similar to BAU, however socio-economic development in the watershed is primarily based on agricultural activities. The agricultural land reform areas managed by the Agricultural Land Reform Office (ALRO) of Thailand will be included, which promotes land use for farmers' livelihoods (Chansawang, 1984; Sreejan, 2024). Furthermore, mining activities, such as coal mining, limestone quarry, and other mineral production, will be implemented in this scenario based on current and future activities. These development fronts are stimulated by incentives (CI=1.1) in ALRO agricultural-reform areas and in recent/future mining footprints, while protected-area constraints remain inactive ("╳") (Table S2).

2.5 LULC change prediction and future scenarios projections

To predict future LULC change (LULCC), the Land Change Modeler (LCM) in TerrSet software was applied following five steps: (1) change analysis; (2) transition potential step and driving variables selection; (3) change prediction; (4) model validation; and (5) future scenarios projections.

2.5.1 Change analysis

Changes between the years 2005 and 2013 were calculated in this panel. The minimum change was set at 600 ha to specify significant changes in the watershed. The LULCC from one category to another was considered and prepared to be selected in the transition potential step.

2.5.2 Transition potential step and driving variables selection

LULC transitions from the change analysis step can be grouped into sub-models based on the same related explanatory drivers of change (Eastman, 2016). A large number of variables may decrease the model's accuracy, while too few variables fail to adequately explain the LULCC (Chen and Yao, 2023).

The initial driving variables (Figure 2) included elevation, slope (degree), distance to roads, distance to streams, distance to agricultural land reform areas, distance to mining (2021), distance to urban and built-up areas (2021), population distribution (2020), and evidence likelihood of LULCC. For the topographic factors, steeper slopes and higher elevations are consistently associated with forest persistence, while low, gentle terrain favors agriculture and settlements (Trisurat et al., 2019). Road expansion increases accessibility, accelerating forest conversion to agricultural and urban and built-up land (Arunsurat et al., 2023). Greater distance from streams stabilizes forest coverage (Trisurat et al., 2019). The ALRO has permitted the area for agricultural activity by the Royal Forest Department, which is responsible for forest zone boundaries in Thailand. Moreover, the ALRO has redistributed state land—largely forest zones—to be used for farming and residential uses (Gine, 2005; Pansak et al., 2024), thus proximity serves as a proxy for policy-driven expansion potential. Additionally, mining activities are the causes of direct LULC change due to the clearing of areas for mining operations. Mining activities induce direct and indirect LULC change and deforestation beyond the immediate site, with those deforestation impacts declining with greater distance from the mining site (Giljum et al., 2022). Urban growth is concentrated near the urban core and along major corridors, with expansion into adjacent zones (Anucharn et al., 2025). The proximity to built-up areas increases conversion likelihood (Arunsurat et al., 2023). Population factors reflect demographic pressure on land conversion (Trisurat et al., 2019) and are the key driving factors of Thailand's LUCC (Wang et al., 2022). Finally, evidence likelihood (Eastman, 2016) was selected, which is the observed probability of land use and land cover (LULC) category changes occurring between an earlier map and a subsequent one.

The Cramer's V coefficients (CVC), a statistical indicator of the degree of relationship or interdependence between variables, was considered as a guideline for selecting these variables, with a CVC greater than 0.15 indicating usefulness (Eastman, 2016). In this study, the selected variables must have an overall CVC above 0.15.

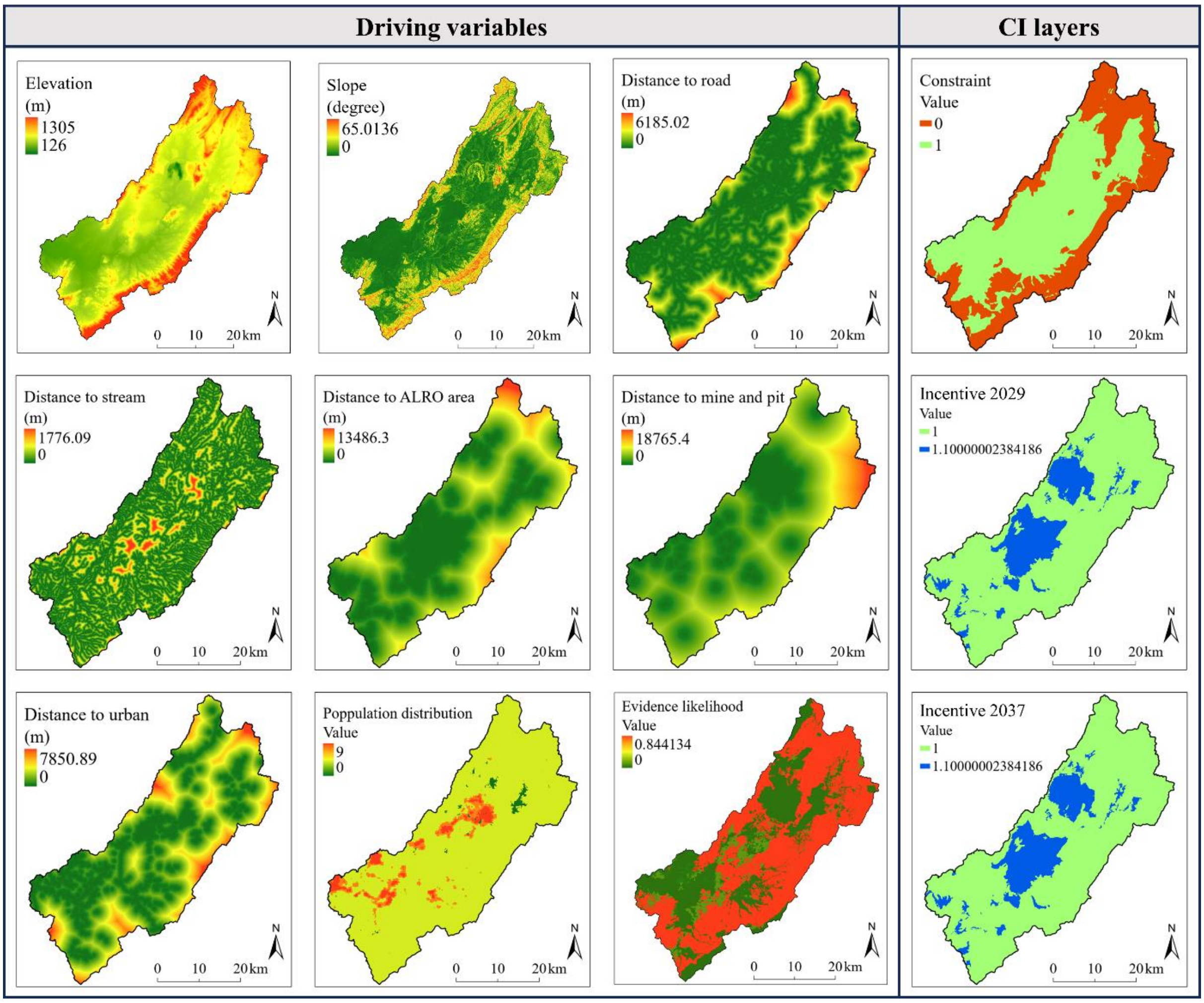

Figure 2. Initial driving variables, and final constraint/incentive layers

The transition potential maps were generated using the multilayer perceptron (MLP) neural network; a feed-forward network with input, hidden, and output layers, trained by back-propagation to learn non-linear relationships between drivers and observed transitions (Hasan et al., 2020; Christensen and Jokar Arsanjani, 2020). In this study, the MLP neural network parameters were set to their default values, utilizing the automatic training and dynamic learning rate. The accuracy rate of each sub-model was set at a minimum of 50%, based on modifications from previous studies (Mishra et al., 2014; Vasanthawada et al., 2023). The skill measure ranges from -1 to 1, with 1 indicating a perfect prediction and -1 indicating worse-than-chance performance (Gharaibeh et al., 2020), with a value between 0 and 1 suggesting the model performed better than random (Christensen and Jokar Arsanjani, 2020).

2.5.3 Change prediction

The predicted 2021 LULC was simulated based on the changes between the actual 2005 and 2013

LULC, using a Markov chain coupled with transition potential maps (Hasan et al., 2020). This step generated two types of predictions: hard and soft prediction models (Eastman, 2016; Gandharum et al., 2024). The hard one refers to predicted LULC where each pixel is assigned to a specific LULC category, which was the approach utilized in this study.

2.5.4 Model validation

The VALIDATE module in TerrSet, which utilizes Kappa statistics was chosen (Saluja et al., 2024). The actual 2021 LULC was selected as the reference source and compared with the projected 2021 LULC, and the results were reported using Kappa indices (Pontius, 2000; Pontius, 2002), such as Kappa Standard (Kstandard), Kappa for No Ability (Kno), and Kappa for Location (Klocation). The Kappa Standard was set at a minimum of 70% (Zadbagher et al., 2018; Leta et al., 2021) for successful validation.

2.5.5 Future scenario projections

After successful calibration and validation, the future scenarios for 2029 and 2037 were predicted. In this step, three scenarios of each future simulation were defined based on the status and value of constraint and incentive layers (CI layer). Values of 0 indicate the area is absolutely constrained (indicating a ‘no-change’ zone), while values of 1 are unconstrainted and values greater than 1 are treated as incentive (Eastman, 2016). The constraint and incentive values in this study were defined based on Arunsurat (2022). For each scenario, only one CI layer—processed from multiple geospatial datasets—was applied. Table S2 shows the CI layer activation in each scenario.

The overall LULCC modeling based on Land Change Modeler (LCM) is summarized and shown as a flow diagram (Figure 3).

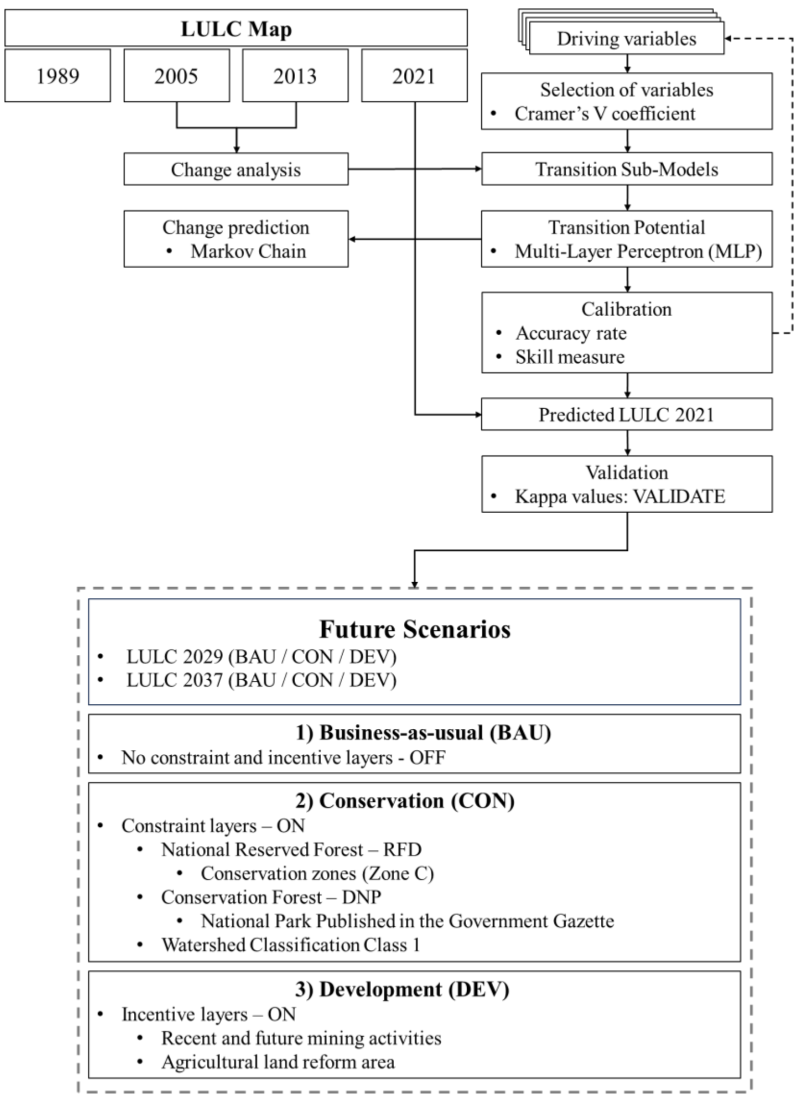

Figure 3. The overall methodology regarding scenario based LULCC prediction

3. RESULTS AND DISCUSSION

After interpretation and classification, the final data yielded overall accuracy of LULC in 1989, 2005, and 2021 of 85.05%, 93.64%, and 91.61%, respectively.

3.1 LULC and change situations in Mae Chang Watershed

The Mae Chang Watershed was primarily covered by forest land, particularly deciduous forest, which covered more than 50% of the total watershed area in 1989 to 2021. Table S3 summarizes the changes in LULC across 1989, 2005, 2013, and 2021. The analysis indicates significant transformations in land use patterns over the 32-year period, driven by a variety of factors such as agricultural expansion, deforestation, and urbanization, as shown in Table S4 and Figure 4.

3.1.1 Agricultural areas

Agriculture represents one of the most dynamic LULC classes. Paddy fields, while starting as one of the largest classes in 1989 at 165.73 km^2 (10.13%), experienced a gradual decline to 160.09 km^2 (9.78%) by 2021. Field crops showed positive trends, increasing slightly from 84.11 km^2 in 1989 to 111.46 km^2 in 2005 (6.81%) and then to 152.65 km^2 in 2013 (9.33%) and 172.21 km^2 (10.52%) in 2021, suggesting a shift toward more intensive agricultural production, mostly consisting of economic crops such as cassava and maize. (Land Development Department, 2015). Similarly, perennial land showed steady growth from 75.47 km^2 (4.61%) in 1989 to 148.93 km^2 (9.10%) in 2021. Orchard areas also saw considerable changes, with an initial small increase from 14.37 km^2 in 1989 to 24.55 km^2 in 2005, followed by a slight decline to 22.34 km^2 by 2021. Other crops remained a minor category throughout the period, with only a modest increase in 2021 to 6.73 km^2 (0.41%). Aquaculture saw a small area of 0.38 km^2 in 2021.

3.1.2 Forest and natural areas

The most significant transformation occurred in deciduous forest, which exhibited a stark decline over time. Starting at 1,070.41 km^2 (65.40%) in 1989, deciduous forests shrank to 821.40 km^2 (50.18%) by 2021. This 15.2% reduction in forest area points to substantial deforestation, likely driven by the expansion of agricultural land, urbanization, and mining activities (Table S4). The evergreen forest class remained relatively stable, covering around 4% of the total area throughout the study period. This might be because the topography and road network are unsuitable for human use, as most of the area belongs to restricted zones such as protected forest areas.

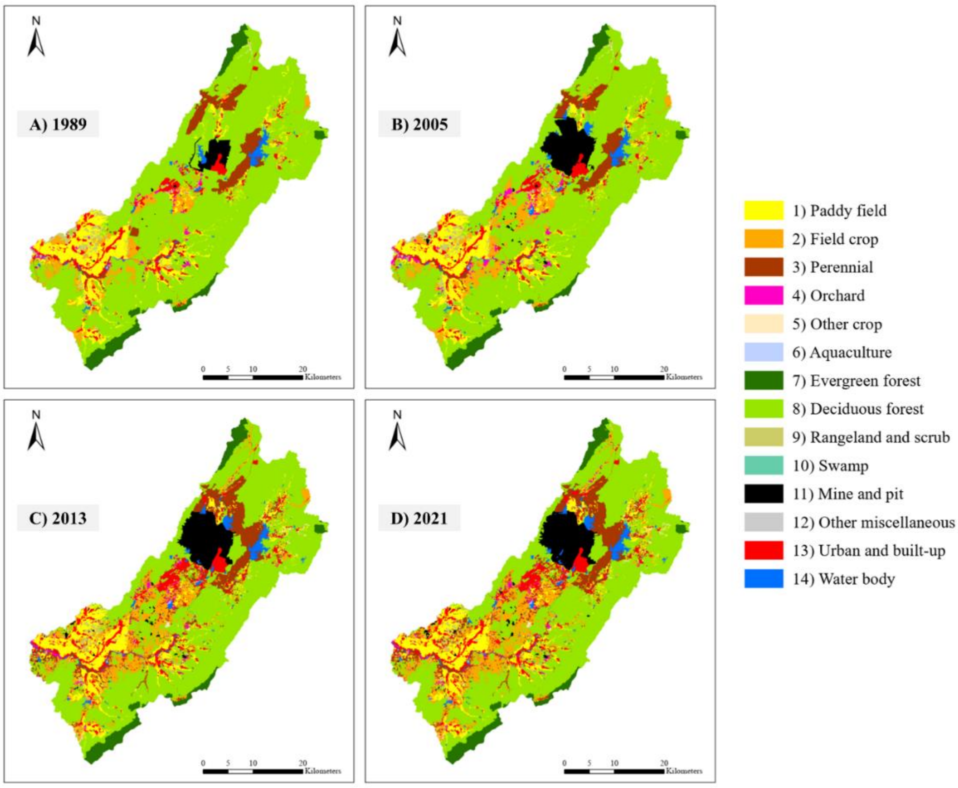

Figure 4. LULC in Mae Chang watershed: A) 1989, B) 2005, C) 2013, and D) 2021

Other natural areas, such as rangeland and scrub, saw a slight decrease from 36.94 km^2 in 1989 to 19.29 km^2 in 2021. Swamp areas, although a very minor component, increased slightly from 0.82 km^2 in 1989 to 2.04 km^2 in 2021.

3.1.3 Mine and pits, and urban areas

Some of the most significant gains were seen in mine and pit areas, which grew from 26.26 km^2 (1.60%) in 1989 to 89.49 km^2 (5.47%) by 2021. This represents a notable expansion in mining and extractive activities, likely contributing to the reduction in forest cover.

Urban and built-up areas also expanded steadily, increasing from 71.95 km^2 (4.40%) in 1989 to 92.67 km^2 (5.66%) in 2021, reflecting the ongoing trend of urbanization. Meanwhile, community relocation is driven by mining companies requiring more space, resulting in new urban areas due to continued mining activities (EGAT, 2022).

3.1.4 Water body

Water bodies also saw a noticeable increase, from 23.00 km^2 (1.41%) in 1989 to 34.90 km^2 (2.13%) in 2021. This is attributed to human activities such as the construction of reservoirs.

3.2 LULCC modeling, calibration, and validation

According to the calibration step, the final five exploratory variables were added to each sub-model, including (1) distance to roads, (2) distance to agricultural land reform areas, (3) distance to mining (2021), (4) distance to urban and built-up areas (2021), and 5) evidence likelihood of LULCC, with the overall CVC more than 0.15 (Table S5).

The four sub-models based on the transition from significant change in the change analysis step were determined, as shown in Table S6. The sub-models were grouped primarily based on the situation occurring in the Mae Chang watershed.

The final sub-model, skill measure, and the accuracy rate of the transition potential process are shown in Table S7. The accuracy rate ranged from 52.87 to 92.40, while the skill measure ranged from 0.3300 to 0.8860. These values coincide with studies in Asia and North America, such as the city of Surat, India (Vasanthawada et al., 2023) and Alabama, United States (Shrestha et al., 2022). The DEF_03 is the highest performing sub-model.

The validation results showed all Kappa variations were greater than 0.8 or 80%. The Kstandard, Kno, and Klocation were 0.8237, 0.8609, and 0.8934, respectively.

3.3 Future scenarios prediction

The LULCC projections reveal significant variations across different future scenarios, Business as usual (BAU), Conservation (CON), and Development (DEV), when compared to the actual LULC in 2021 (Table S8 and Figure 5).

For the BAU scenario, paddy fields increased from 160.09 km^2 (2021) to 173.69 km^2 (2029) and 180.42 km^2 (2037). Field crops expanded to 200.70 km^2 (2029) and 207.19 km^2 (2037). Perennial crops showed the strongest growth, rising from 148.93 km^2 (2021) to 271.13 km^2 (2029) and 319.06 km^2 (2037). Evergreen forest remained stable, while deciduous forest declined from 821.40 km^2 (2021) to 637.87 km^2 (2029) and 562.46 km^2 (2037). Mines and pits increased to 102.04 km^2 (2029) and 107.98 km^2 (2037). Urban and built-up areas rose to 104.57 km^2 (2029) and 112.45 km^2 (2037).

For the CON scenario, paddy fields increased to 173.71 km^2 (2029) and 180.43 km^2 (2037). Field crops reached 200.68 km^2 (2029) and 207.19 km^2 (2037). Perennial land grew to 271.10 km^2 (2029) and 319.02 km^2 (2037). Evergreen forest was stable while deciduous forest fell to 637.87 km^2 (2029) and 562.49 km^2 (2037). Mines and pits increased to 102.07 km^2 (2029) and 107.94 km^2 (2037). Urban and built-up areas increased to 104.58 km^2 (2029) and 112.49 km^2 (2037).

For the DEV scenario, paddy field rose to 173.71 km^2 (2029) and 180.43 km^2 (2037). Field crop expanded to 200.68 km^2 (2029) and 207.19 km^2 (2037). Perennial reached 271.10 km^2 (2029) and 319.02 km^2 (2037). Evergreen forest was still stable while deciduous forest decreased to 637.87 km^2 (2029) and 562.49 km^2 (2037). Mines and pits increased 102.07 km^2 (2029) and 107.94 km^2 (2037). Urban and built-up areas increased to 104.58 km^2 (2029) and 112.49 km^2 (2037).

Across all scenarios, the largest transitions are from deciduous forest to perennial land and from deciduous forest to field crop, increasing from 2029 (≈79-81 km^2 and ≈78-79 km^2) to 2037 (≈115-116 km^2 and ≈95-96 km^2) (Figure 6). Field crop to perennial also rose (≈44-45 to ≈56 km^2). Conversions of deciduous forest to paddy field, urban and built-up areas, and mines and pits increased modestly by 2037 (to ≈17, ≈23, and ≈18-20 km^2, respectively). Some small areas of field crops are transformed to deciduous forest areas (≈8-11 km²). The projected situations coincide with the studies of Arunsurat et al. (2023) and Saluja et al. (2024), conducted in the northern and northeastern parts of Thailand, whose results show deforestation and agricultural expansion, particularly in the BAU scenarios.

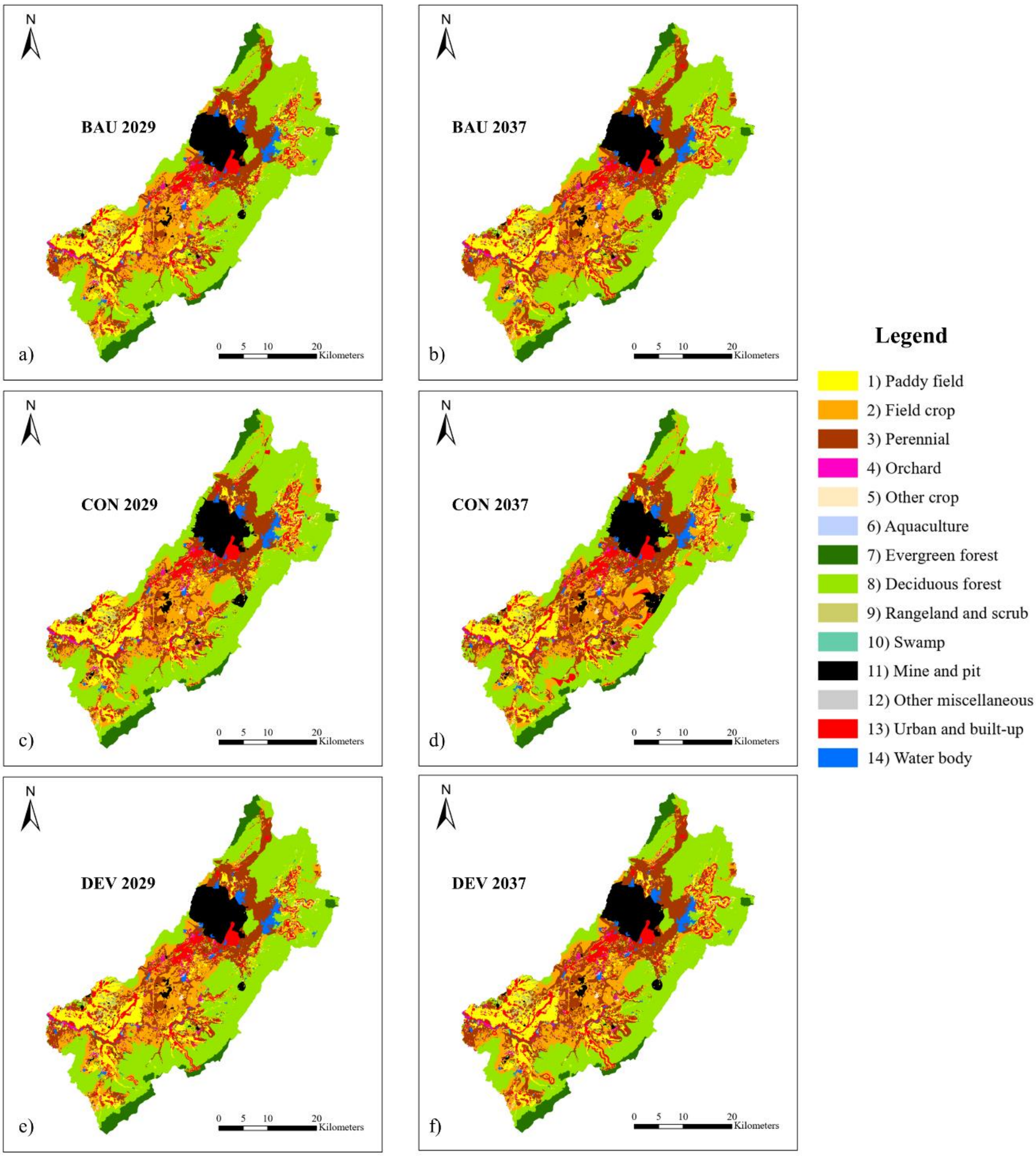

Figure 5. Future scenarios for 2029 and 2037: a), b) BAU scenarios; c), d) CON scenarios; e), f) DEV scenarios

Arunsurat et al. (2023), which studied in Chiang Mai-Lamphun basin in Chiang Mai and Lamphun Provinces, located near the Mae Chang Watershed, demonstrates scenario-dependent quantities of change. Under the Ecological Protection Scenario (EPS), forest cover is maintained at approximately 61.65% in both periods, whereas the Business-as-Usual (BaU) and Baseline Development Scenario (BDS) pathways decline to about 54% by 2050, with greater allocation to agricultural and built-up uses. In the Mae Chang watershed projections, the dominant transitions are likewise from deciduous forest to perennial land and to field crops; however, total areas by class are essentially indistinguishable across BAU, CON, and DEV in 2029 and 2037 (Table S8), indicating that scenario effects are negligible in quantity and act primarily by spatially reallocating change rather than altering overall amounts. This might happen because this study did not adjust the Markov demand but mainly relied on CI layers, so the total area can be similar across all scenarios. The results from this study also coincide with Abbasnezhad et al. (2023), which used the same Markov matrix for several scenarios.

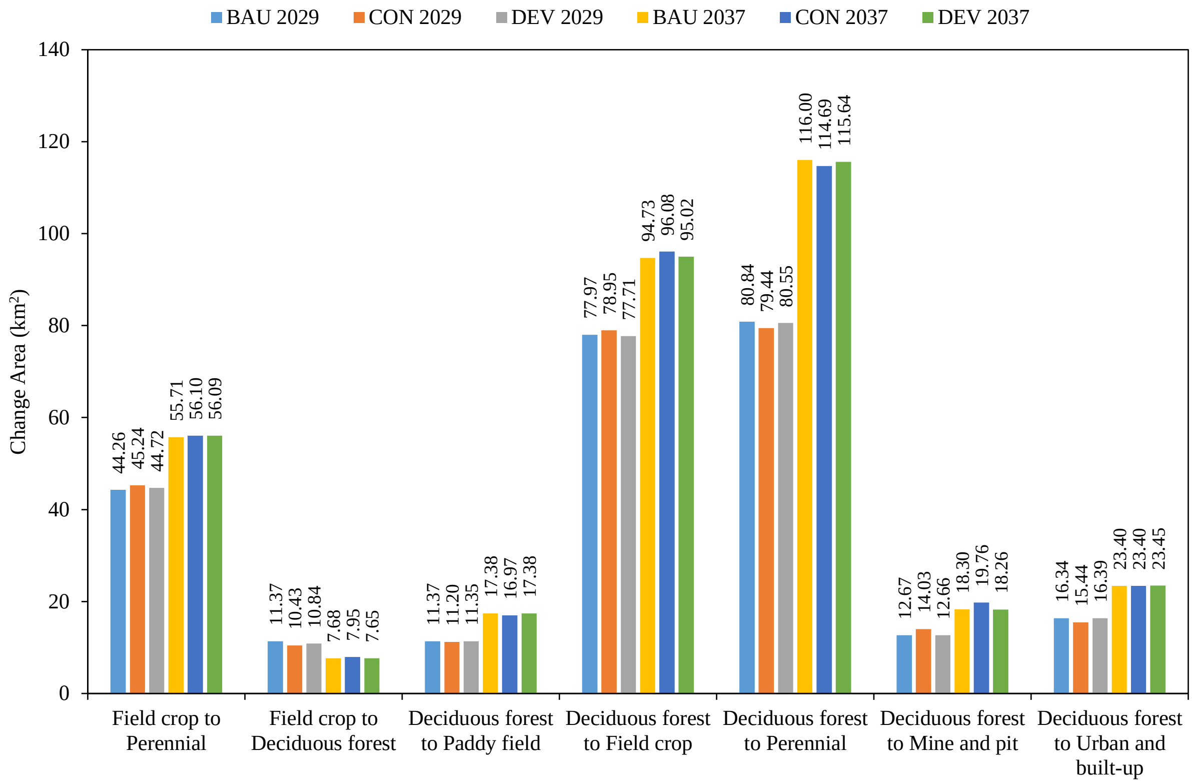

Figure 6. LULCC primary transition from actual LULC 2021 of each scenario

Even though the results in terms of the quantity of change showed a similar pattern across all scenarios (Table S8 and Figure 6), there are significant differences when considering the spatial distribution of the projected LULCC (Figure 7). In the BAU and DEV scenarios, where constraints (protected and restricted areas) are not enforced, deforestation may continue in those areas.

The LULCC, particularly forest loss and agricultural expansion, can exacerbate soil erosion (Paiboonvorachat and Oyana, 2011), increasing sediment yield and nutrient export, which in turn degrade water quality (Chotpantarat and Boonkaewwan, 2018). Mining activities similarly contribute to water quality deterioration (Woon et al., 2021). While such developments may enhance human well-being, they also impose significant environmental costs.

Under the CON scenario, the predominance of evergreen and deciduous forests in the headwatershed supports preservation. Evidence from Northern Thailand indicates that protected areas mitigate forest loss and fragmentation, whereas unprotected landscapes near urban-agricultural frontiers are more susceptible to degradation—reinforcing the role of the CON scenario in safeguarding core habitats (Lee et al., 2022). This underscores the importance of protected and restricted zones, which not only conserve headwater sources but also sustain ecosystem services such as water provision (Chotikasathira, 1988).

3.4 Uncertainties and limitations

LULCC modeling is constrained by the inherent complexity of environmental systems, uncertainties in data, and the difficulty of anticipating human decision-making that shapes land transformation (Bachri et al., 2024). Our results may carry uncertainty from both data and modeling factors. First, although the land use nomenclature was defined with more detail, satellite imagery alone cannot always capture this level of precision. Therefore, we incorporated very high-resolution imagery from both aerial and satellite sources to ensure the highest possible accuracy of the LULC data input into the model. Second, by analyzing only the dominant transitions for this watershed, some minor or dispersed LULC changes were omitted and may underestimate localized impacts while leaving landscape-scale totals broadly unchanged. Third, scenario construction relied on activating constraint and incentive layers; we did not vary land-demand (class quantities) by scenario. Consequently, BAU/CON/DEV differences should be interpreted primarily as spatial reallocation of change rather than as large shifts in total area by class. Finally, some drivers (e.g., gridded population distribution) were sourced from global products with an effective resolution coarser than 30 m, which can misalign with local patterns and misallocate future changes near settlements. Mining also induces rapid, localized changes in topography (elevation/slope). However, these driving variables were excluded because their Cramer's V values did not meet our selection threshold, which may result in underrepresentation of future LULC change. Therefore, given the inevitable uncertainties in land-use change modeling, outputs from the Land Change Modeler must be treated as approximations and interpreted alongside local context and variations in land-use processes (Bachri et al., 2024).

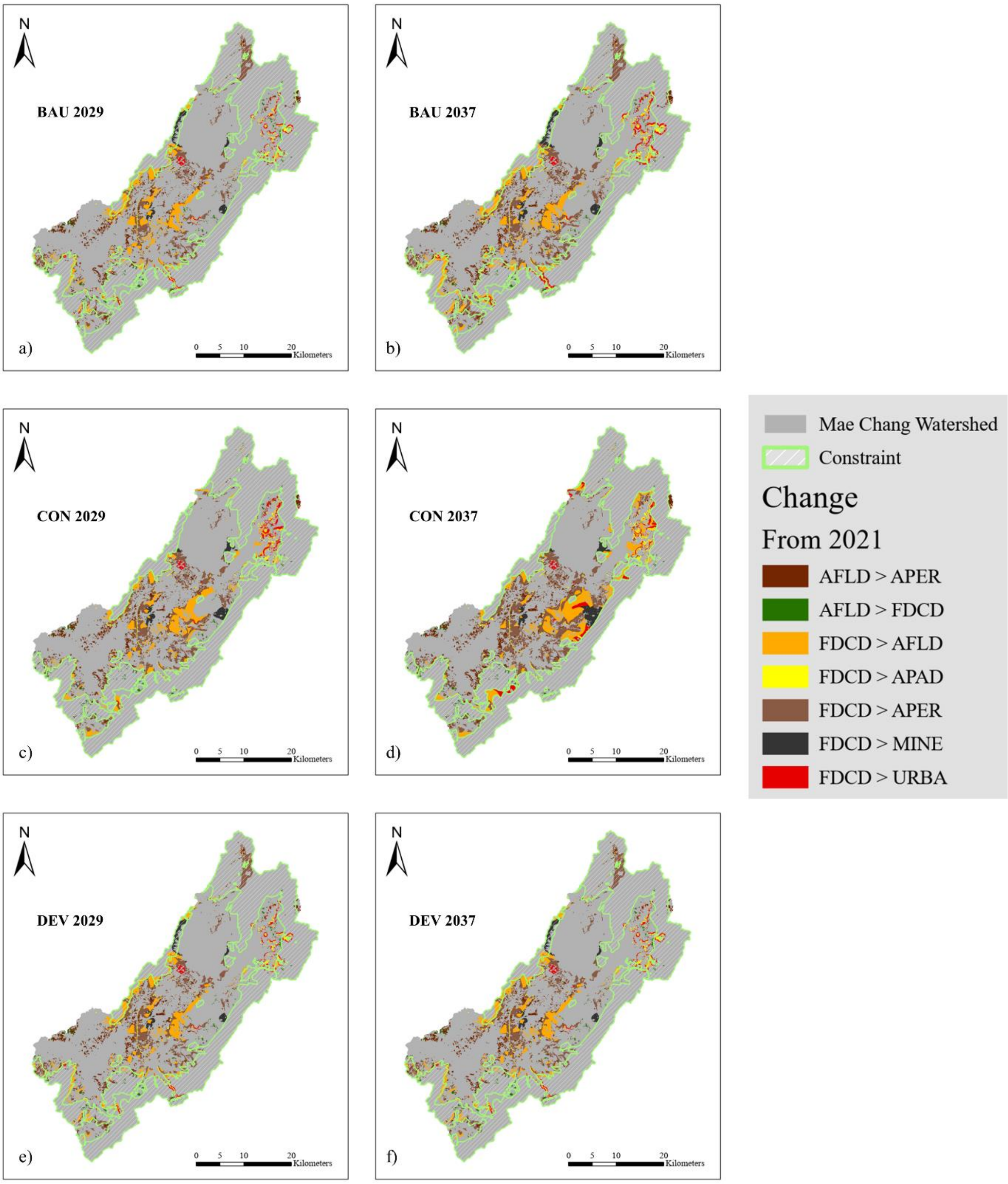

Figure 7. Primary LULC changes from 2021 for each scenario: a) BAU 2029, b) BAU 2037, c) CON 2029, d) CON 2037, e) DEV 2029, and f) DEV 2037.

4. CONCLUSION

The data highlights significant trends in land use change over the period from 1989 to 2021, with the deciduous forest cover in the watershed having declined substantially by 23.3%. Over the same period, field crops expanded by 104.7%, perennial crops by 97.3%, mines and pits by 240.8%, and urban areas by 28.8%, reflecting significant shifts in land use dynamics. Meanwhile, the stability of evergreen forests points to some level of environmental conservation. These LULC changes suggest both development-driven land conversions and efforts to sustain agricultural productivity.

Moreover, this study employed Multilayer Perceptron (MLP) Neural Network, Markov Chain modeling, coupled with transition potential maps and CI layers establishment, to simulate future LULC scenarios for 2029 and 2037 under Business-As-Usual (BAU), Conservation (CON), and Development (DEV). The findings underscore the importance of sustainable land management policies to mitigate the impact of human activities on natural ecosystems, particularly with the growing demand for land resources, with CON able to constrain deforestation, particularly in protected, conserved, and restricted area. This is crucial to ensure the well-being of both human and ecological systems in the future. Since Thailand has also has the National Biodiversity Action Plan 2023-2027, the targeted and recommended actions are to expand and strengthen protected areas and OECMs (Other Effective Area-Based Conservation Measures), prioritize high-biodiversity and ecosystem-service sites, ensure effective, resource management and monitoring, connect areas via ecological corridors, uphold participatory governance and rights, implement continuous, outcome-tracked restoration, and focus management on ecosystem integrity, connectivity, and sustainable benefits (Office of Natural Resources and Environmental Policy and Planning, 2024). It is crucial that these actions are followed.

Due to the unavoidable uncertainties in land-use change modeling, the results from the Land Change Modeler are best treated as approximations. Future studies should integrate finer-resolution datasets and local socio-environmental factors to improve predictive reliability, for example, population income, agricultural land suitability, local bias correction from global to local correct climatic factors (historical and future scenarios).

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AUTHOR CONTRIBUTIONS

Conceptualization, Methodology, Software, Validation, Formal Analysis, Investigation, Resources, Data Curation, Writing-Original Draft Preparation, Writing-Review and Editing, Visualization: Vongvassana S.; Conceptualization, Resources, Data Curation, Supervision, Project administration, funding acquisition: Pattanakiat S.; Supervision: Tabucanon AS.; Supervision, Data Curation: Chiyanon T.; Supervision: Nakmuenwai P.; Supervision: Lawawirojwong S.; Investigation, Resources: Boonriam W.; Data Curation, Resources: Chinsawadphan P.; Conceptualization, Writing-Review and Editing, Supervision: Phutthai T.

DECLARATION OF CONFLICT OF 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.

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