



Research article

Integrated assessment of climate change and land use impacts on multi-crop vulnerability in Mun River Basin, northeast Thailand

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Abstract

Importance of the work: The quantification of climate and land use change effects on multi-crop systems can inform strategic agricultural adaptation.

Objectives: To evaluate the combined effects of climate (CMIP5/CMIP6) and land use change (LUC) on multi-crop economic output and to determine spatial susceptibility across the Mun River Basin, northeast Thailand.

Materials and Methods: The decision support system for agrotechnology transfer (DSSAT) model and the land-similarity-unit technique were applied to assess four major cash crops: rice, maize, cassava and sugarcane. Land use was projected using a cellular automata-Markov chain model. Economic effects were quantified across four scenarios: baseline, climate change (CC)-only, LUC-only and integrated CC & LUC.

Results: The CC-only scenario caused an 8.9% reduction in total output. Rice and maize had very unstable yields (coefficient of variance up to 43.0%). The LUC-only scenario increased output by 4.5%, driven by converting rice paddies to higher-value crops. The integrated effect resulted in a net reduction of 4.4%. District-level analysis revealed non-uniform responses: uplands experienced output increases (+22.2% in Sangkha), reflecting successful adaptation, whereas lowlands showed aggravated losses (-15.0% in Kaset Wisai).

Main finding: Strategic land use adaptation can offset economic losses from climate change. Spatial targeting is critical and vulnerability remains high in rainfed lowlands where crop conversion is unsuitable.

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Introduction

Global climate change (CC) exerts foundational pressure on agricultural production, primarily through the intensified global water cycle (Ahmed and Stockle, 2017; Bezner Kerr et al., 2022). This process generates frequent, severe hydrological events, necessitating spatial and temporal redistribution of water resources (Chen et al., 2017). CC impacts factors such as temperature, precipitation patterns and the overall hydrological cycle. The Intergovernmental Panel on Climate Change (IPCC) has projected that such extreme events will intensify as warming continues. (Khadka et al., 2021b).

Interpreting these consequences requires modeling strategies that extend beyond temperature or precipitation analysis (Turrall et al., 2011). Crop yield response models, such as the decision support system for agrotechnology transfer (DSSAT) system, translate regional climatic variations and stress combinations into potential production outcomes (Lobell et al., 2011). Advances in crop modeling allow for detailed analysis of the complex relationships between climate and crops (Di Paola et al., 2016; Nendel et al., 2018; Seidel et al., 2018). Prior investigations focusing on rice production have demonstrated substantial, region-dependent effects of climate change on yields (Horie, 1993; Matthews et al., 1995; Jin et al., 1995; Horie et al., 2008; van Oort and Zwart, 2018; Das et al., 2020; Debnath et al., 2021; Saravanakumar et al., 2022).

In addition to CC, land use change (LUC) alters regional hydrology and agricultural productivity (Bhandari et al., 2022). While some studies have assessed combined CC and LUC effects on streamflow (Wang et al., 2013; Mehdi et al., 2015), water quality (Mehdi et al., 2015; Ross and Randhir, 2022) and groundwater (Ghimire et al., 2021), a knowledge gap persists in quantifying their integrated, non-uniform effects on multi-crop economic output. Examining the mutual dependence between these factors is essential, as their combined effects often differ from individual influences.

The Mun River Basin in Northeast Thailand exemplifies this challenge. Despite ample annual precipitation (1,200–1,600 mm), this agricultural region is highly susceptible to seasonal droughts that cause widespread crop failure (Abatan et al., 2023), which substantially diminishes farmer prosperity (Pavelic et al., 2012). Consequently, researchers have become interested in exploring future climate scenarios for this region (Khadka et al., 2021b; Sridhar et al., 2021; Supharatid et al., 2022). Other research has investigated climatic variability

effects on rice production (Ahmed et al., 2017; Limsakul, 2019). However, the early studies relied on outdated climate projections or non-spatial, single-field simulations (Babel et al., 2011; Mainuddin et al., 2012). Later work used IPCC-AR5 projections (Shrestha et al., 2017; Boonwichai et al., 2019; Arunrat et al., 2020); however, no published studies have addressed crop production using recent CMIP6 data. Furthermore, most adaptation research has focused on planting dates or fertilizer use (Babel et al., 2011; Mainuddin et al., 2012; Boonwichai et al., 2019); thus, the potential of crop-type conversion—a primary land use decision—remains largely unquantified.

Therefore, the current study addressed this gap by providing an integrated assessment of multi-crop vulnerability to CC and LUC at the basin scale. The spatially explicit framework coupled the DSSAT crop model with the land-similarity-unit (LSU) technique to simulate economic output for rice, cassava, sugarcane and maize. The framework incorporated a multi-model ensemble of CMIP5 and CMIP6 climate scenarios, interpreted alongside a CA-Markov model for land use. The objectives were: 1) to quantify the basin-wide economic effect of combined CC and LUC; and 2) to analyze the spatial heterogeneity in multi-crop vulnerability. The outcomes should help to establish strategic crop conversion as a central adaptive capacity, providing location-specific data to guide management.

Materials and Methods

Analytical framework

The analytical framework evaluated the integrated effects of climate and LUC on crop production (Fig. 1). The process began with the preparation of essential input data—encompassing climate, soil, land use and crop yield statistics—to configure the DSSAT model. Historical crop yield data were used for model calibration and validation.

The future climate scenarios incorporated projections from CMIP5 and CMIP6 models, while the land use change scenarios were generated using CA-Markov simulation. These scenarios served as inputs for the DSSAT model. Subsequently, model outputs were analyzed to quantify the impacts of climate and land use change on crop production. Finally, the results were aggregated to evaluate the cumulative impact on agricultural production at both the basin and district scales.

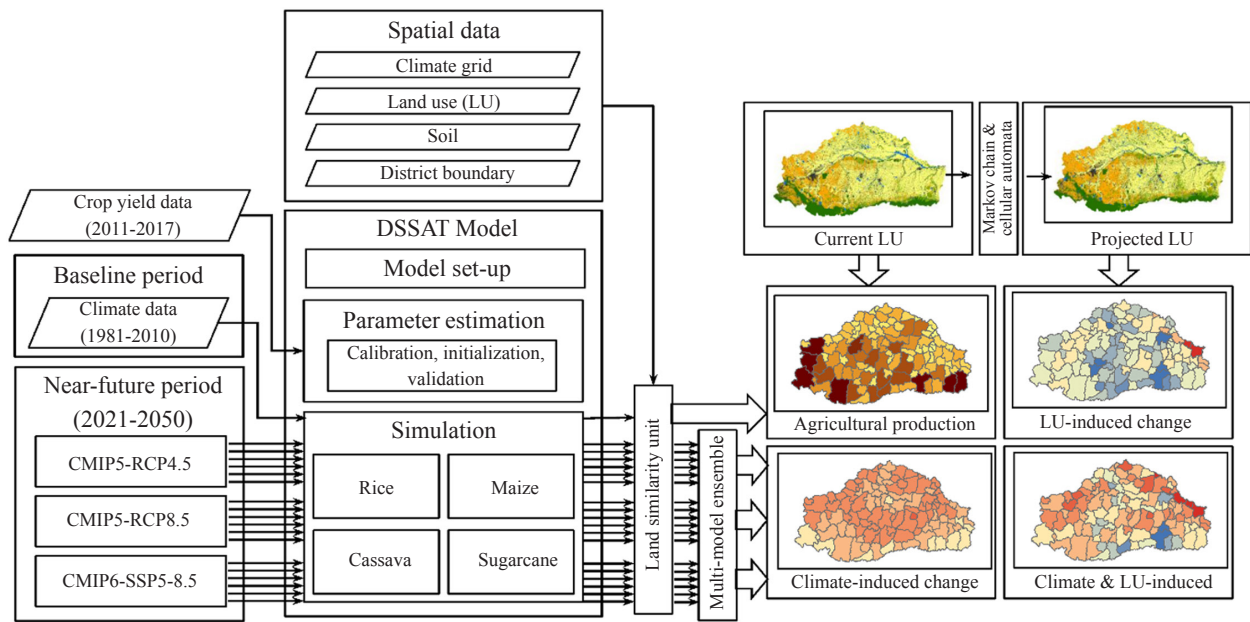


Fig. 1 Schematic representation of the spatially explicit analytical framework applied to assess combined impacts of climate and land use (LU) change on multi-crop production

Study area

The study focused on the Mun River Basin (Fig. 2), the largest river basin in Northeast Thailand and a major right-bank tributary of the Mekong River. The entire basin covers approximately 71,000 km², characterized mostly by gently undulating terrain within the Korat Plateau. The region

experiences a tropical savanna (Aw) climate with mean annual rainfall in the range 800–1,800 mm.

The specific study area, encompassing 53,000 km² (the upper and middle drainage basins, Fig. 2), was selected due to its elevated agricultural activity and heightened susceptibility to climate variability. This defined area has four major cash crops: rice, cassava, sugarcane and maize.

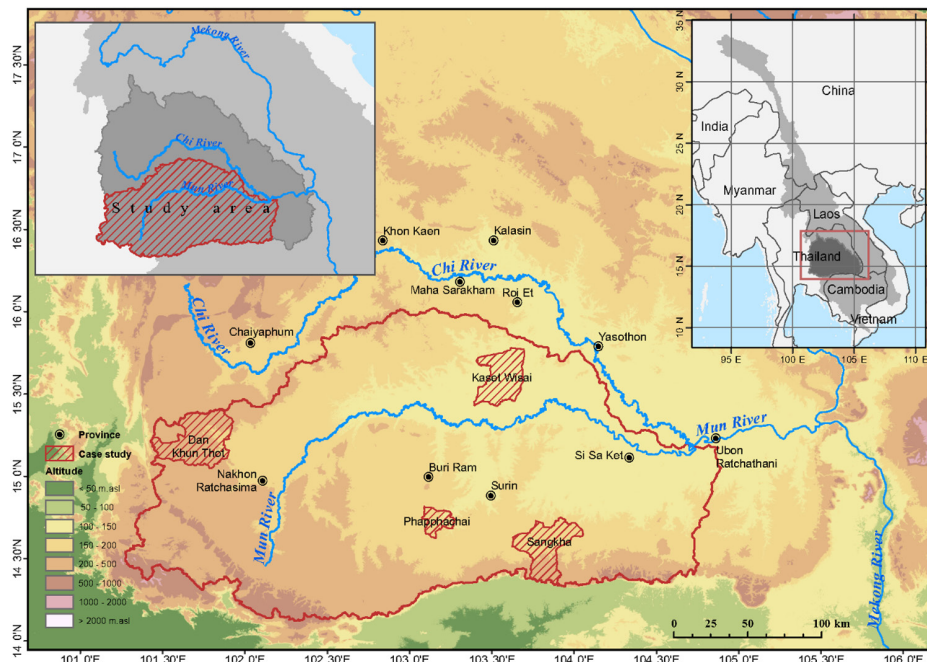


Fig. 2 Study area within Mun River Basin, showing selected district-level case studies: Dan Khun Tod district, Nakhon Ratchasima province; Phlaphlachai district, Buriram province; Sangkha district, Surin province; and Kaset Wisai district, Roi Et province

Decision support system for agrotechnology transfer model configuration and calibration

The crop modeling strategy utilized the DSSAT model, version 4.7.5 (Hoogenboom et al., 2020). This section details data acquisition, spatial configuration and calibration that ensured the model's reliability for basin-scale assessment.

Data acquisition and preparation

The DSSAT model required daily rainfall and maximum and minimum temperatures as climate data. Rainfall data from 43 stations in the study area were utilized. These data were processed using the inverse distance weighting method to create 91 grids, each with a 0.25° resolution (matching the resolution of the projected climate data). Climate data for the 30 year baseline period (1981–2010) were obtained from stations run by the Thai Meteorological Department.

Soil and land use data were obtained from Thailand's Land Development Department (LDD). Up-to-date land use maps from 2019 were compiled and grouped into five main categories: agriculture, forest, urban, water and other. The main crops within the agriculture category (rice, cassava, sugarcane, maize and perennial plants) were retained. These grouped land use data, along with spatial data for the main crops, were converted into raster files with a grid size of 0.1° (approximately 1 km). The LDD's soil map provided the locations of different soil types and their properties.

Crop yield statistics were imperative for model setup and validation. District-level data for rice (2011–2017), maize (2012–2017) and cassava (2011–2017) were acquired from the Office of Agricultural Economics. Provincial-level sugarcane yield data for 2006–2018 was obtained from the Office of Cane and Sugar Board.

Model configuration

The DSSAT model executes point simulations. The LSU technique was implemented to adapt this for basin-scale assessment and to account for spatial variability. The study area was discretized into grid cells of 0.1° . The 91 climate data grids, originally at a resolution of 0.25° , were resampled to 0.1° .

Overlaying climate, land use and soil maps defined unique crop-soil-climate attributes, yielding 4,368 LSUs. These incorporated four major cash crops, 12 soil textural classes and 91 climatic grids. This approach required 4,368 simulation runs for each climatic dataset.

The DSSAT crop simulators and genetic coefficients (GCs) were selected based on regional cultivar prevalence (Ekasingh et al., 2008) and prior validation:

- Rice was modeled using the CERES-Rice simulator parameterized with the KDML105 GC, reflecting the dominant rainfed cultivar in northeast Thailand (Kerdsuk, 2002; Wikarnpapraharn and Kositsakulchai, 2010).
- Maize utilized the CERES-Maize simulator with the Suwan GC, established for its suitability under tropical conditions (Asadi and Clemente, 2003; Babel et al., 2018).
- Cassava used the CSCAS model with the Rayong 9 GC, due to its regional adaptability (Sarawat et al., 2000; Kumsueb and Jintrawet, 2020).
- Sugarcane was simulated using the CANEGRO model parameterized with the Khon Kaen 3 GC, selected as a representative long-season cultivar (Kapetch et al., 2016).

Calibration and validation

Model performance was evaluated using standard statistical indicators (Legates and McCabe, 1999): the coefficient of determination (R^2), the Willmott's index of agreement (d-value; Willmott, 1982) and the normalized root mean square difference (nRMSD; Khakbaz et al., 2012).

Data from 2015 to 2017 were used for calibration, while data from 2012 to 2014 were used for validation. Since only provincial-level data were available for sugarcane, all sugarcane data from 2012 to 2017 were incorporated into the calibration process. The calibration involved iteratively fine-tuning crop parameters (GCs) and adjusting initial soil water and nutrient levels.

Table 1 presents the model performance indicators, which indicate satisfactory overall model performance for regional-scale modeling. A high R^2 value (0.95–0.98) indicates a strong correlation, a moderate d-value (0.33–0.68) suggests a reasonable level of agreement and an nRMSD below 20% is considered acceptable for crop yield simulation (Yang et al., 2014).

Land use and climate scenarios

Climate change scenarios

The assessment of future climatic effects depended on the outputs of global climate models (GCMs). The current study utilized a robust multi-model ensemble approach to capture the full range of uncertainty associated with GCMs (Winkler, 1989; Wu and Levinson, 2021).

Table 1 decision support system for agrotechnology transfer model performance on spatial simulation of crop yields

Crop	Period	R ²	d-Value	nRMSD
Rice (26,514 km ²)	2012–2014	0.97	0.33	17.1%
	2015–2017	0.96	0.40	11.7%
Maize (709 km ²)	2012–2014	0.98	0.49	14.0%
	2015–2017	0.95	0.51	13.2%
Cassava (5,452 km ²)	2012–2014	0.96	0.58	23.1%
	2015–2017	0.98	0.68	15.7%
Sugarcane (3,312 km ²)	2012–2017	0.97	0.55	17.7%

Cultivated area provided in parentheses, based on land use data from 2019. Recorded yields were obtained from district-level data for rice, maize and cassava, provincial-level data for sugarcane. Validation period used data from 2012 to 2014, while calibration period utilized data from 2015 to 2017 (2012–2017 for sugarcane). Model performance evaluated using statistical indicators: R² (coefficient of determination), d-value (Willmott's index of agreement) and nRMSD (normalized root mean square difference).

The analysis incorporated climatic data from the fifth and sixth phases of the Coupled Model Intercomparison Project (CMIP5) and the more recent CMIP6. The six superior-performing models from each phase were chosen specifically for their demonstrated ability to simulate accurately the regional climate of the Mun River Basin, based on prior ranking via compromise programming (Khadka et al., 2021a). The assessment spanned the near-future period (2021–2050) against the baseline climate (1981–2010), providing immediate relevance for regional planning (Tingsanchali et al., 2022).

The scenarios incorporated were the Representative Concentration Pathways 4.5 (RCP4.5) and 8.5 (RCP8.5) scenarios from CMIP5 and the Shared Socioeconomic Pathway 5 under RCP8.5 (SSP5-8.5) scenario from CMIP6. The resulting 18 projected datasets provided the rainfall (Fig. 3) and temperature (Fig. 4) series required by the DSSAT model.

Land use change scenarios

Future land use was modeled using the integrated cellular automata-Markov chain (CA-Markov) model (Kositsakulchai et al., 2021). This assessment centered on the business-as-usual (BAU) pathway, assuming no external intervention. Markov Chain analysis computes historical transition probability (Bell, 1974), which is then spatially allocated using cellular automata rules (von Neumann and Burks, 1966).

To project future land use for 2045, the land transition probability for a 7 year period was derived from the LDD land use maps for 2010 and 2017. The current or initial land use was represented by the LDD land use map for 2019 (LDD2019, Fig. 5A). The CA-Markov model simulated the land use pattern for the projected year 2045 (BAU2045, Fig. 5B), applying these probabilities to the current configuration (LDD2019) (Penny et al., 2022).

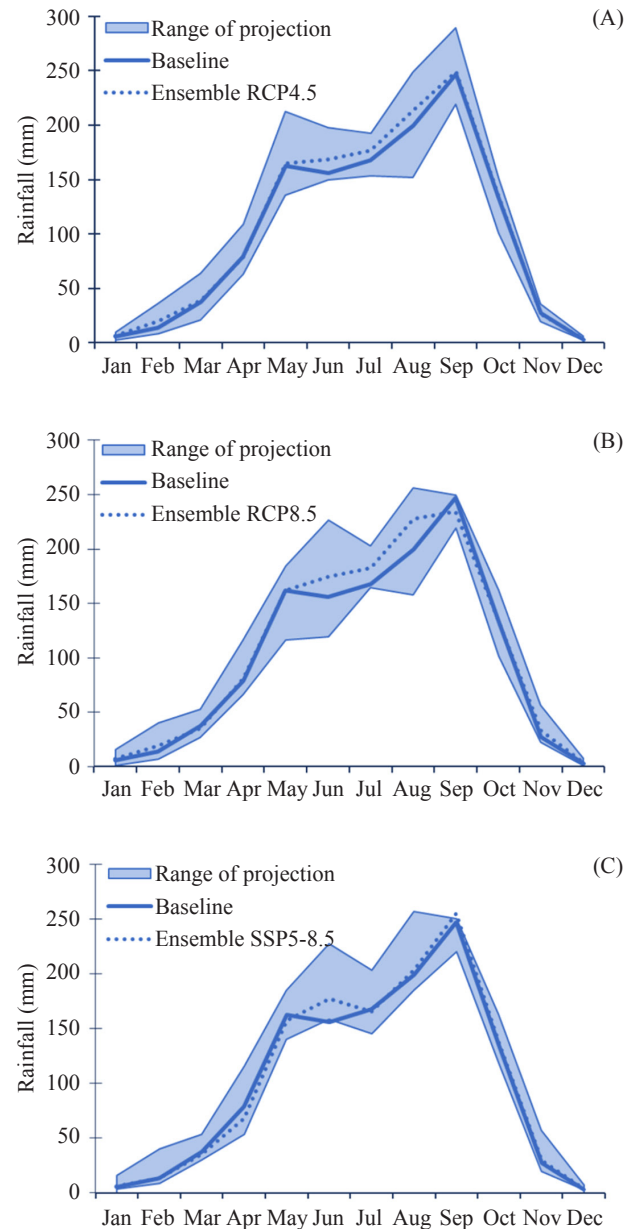


Fig. 3 Mean monthly rainfall over Mun River Basin for: (A) CMIP5-RCP4.5 scenario, (B) CMIP5-RCP8.5 scenario; (C) CMIP6-SSP5-8.5 scenario

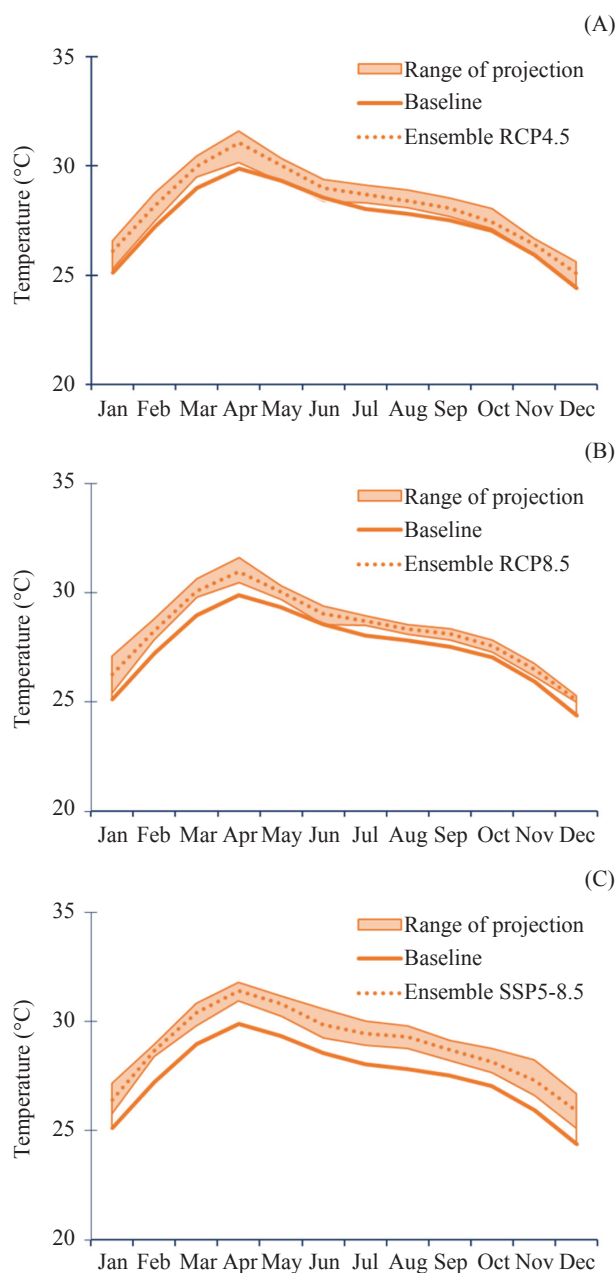


Fig. 4 Mean monthly temperature over Mun River Basin for:(A) CMIP5-RCP4.5 scenario, (B) CMIP5-RCP8.5 scenario; (C) CMIP6-SSP5-8.5 scenario

Assessment of combined impacts

The evaluation quantified economic vulnerability by integrating physical yield simulations with economic data. The output metric and scenario design were structured to isolate the effects of climate and land use drivers.

Output metric and economic conversion

Simulated biological yields (in kilograms per hectare) for

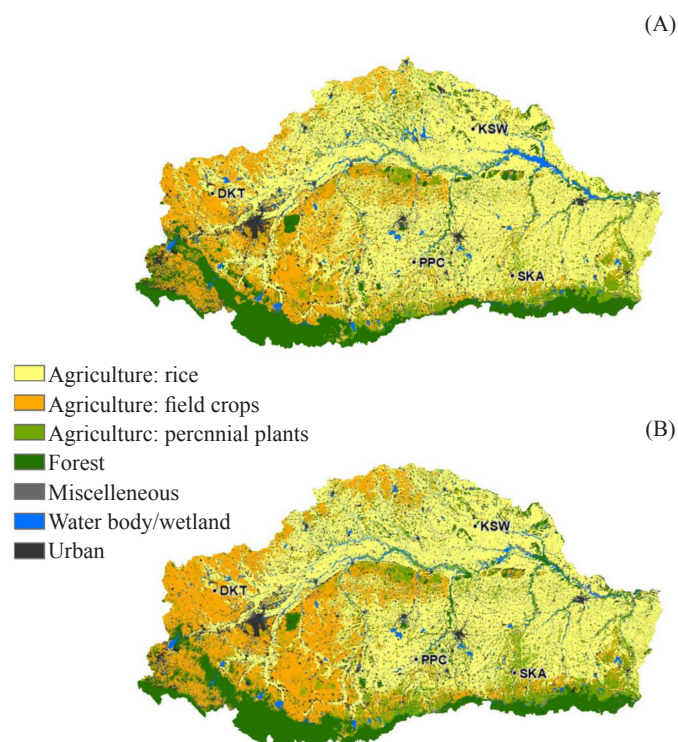


Fig. 5 Land use in study area of Mun River Basin: (A) land use in 2019 from Land Development Department of Thailand (LDD2019); (B) projected land use in 2045 under business-as-usual pathway (BAU2045)

each LSU were converted into a unified economic indicator: total agricultural income (million USD). Calculations utilized 5 year average local unit prices (2015–2019) obtained from the Office of Agricultural Economics: rice (USD 369.84 /t), maize (USD 243.95 /t), cassava (USD 60.24 /t) and sugarcane (USD 25.54 /t). Income from perennial plants (natural rubber) was derived based on area at USD 2,840.9/ha.

Scenarios for quantification

The analysis carried out a systemic comparison using four distinct scenarios: 1) Baseline, using baseline climate (1981–2010) combined with current land use (LDD2019); 2) climate change (CC-only), using projected near-future climate (2021–2050) combined with LDD2019 land use; 3) land use change (LUC-only), using baseline climate combined with projected land use (BAU2045); and 4) integrated impact (CC & LUC), using projected climate combined with BAU2045. This integration followed a sequential coupling approach. First, the CA-Markov model projected the spatial configuration of future land use (BAU2045). Then, this projected map was overlaid with soil and climatic grids to define specific LSUs, which served as direct inputs for the DSSAT simulation to quantify economic output.

Spatial analysis

The economic indicator was analyzed at two scales: 1) the basin level, summarizing overall economic vulnerability within the basin boundary; and 2) the district level, utilizing administrative boundaries to reveal localized capacity and heterogeneous effects. This facilitated the identification of critical areas across four case studies: Dan Khun Tod (DKT), Phlappalachai (PPC), Sangkha (SKA) and Kaset Wisai (KSW).

Results

The results section presents the quantitative findings derived from the integrated modeling framework, detailing the effects of land use change (LUC), climate change (CC) and their combined influence on agricultural output across the Mun River Basin.

Land use change projections

The CA-Markov model projected substantial changes within the agricultural land use class under the BAU2045 scenario. As summarized in Table 2, the total agricultural area remained nearly constant, experiencing only a minimal +0.2% change in total area.

Table 2 Total area (km²) of land use in 2019 (Land Development Department, LDD2019) and projected land use in 2045 under business-as-usual pathway (BAU2045)

L and use class	LDD2019	BAU2045	Change
Agriculture			
Rice	26,514	23,930	-2,584 (-9.7%)
Field crops	9,473	11,004	1,531 (+16.2%)
Perennial plants	3,858	4,657	799 (+20.7%)
Other	23	370	347 (>100%)
Subtotal	39,868	39,961	93 (+0.2%)
Forest	6,161	5,905	-256 (-4.2%)
Urban	3,711	3,788	78 (+2.1%)
Water body	1,597	1,669	72 (+4.5%)
Miscellaneous	1,629	1,643	14 (+0.9%)
Total	52,966	52,966	

This aggregate stability masked major internal shifts within the agricultural subclass. For example, rice cultivation declined by 9.7% (2,584 km² loss). This reduction was offset by corresponding expansion in higher-value crops. Field crops increased by 16.2% (1,531 km² gain) and perennial plants by 20.7% (799 km² gain).

Fig. 5 confirmed this spatial trend, demonstrating the substitution of lowland rice areas with field crops and perennial plants, primarily in the western and southern upland zones of the basin. This result established the baseline human adaptation trend for the assessment of future climate effects.

Individual crop susceptibility to climate change

The isolated effect of climate change was determined by simulating yields under future climate scenarios using the current land use (LDD2019). Ensemble data projected consistent yield declines across all four major crops, ranging from 9.4% to approximately 14.7%.

Susceptibility differentiated notably by crop type, as measured by the coefficient of variation (CV) for yield instability (Fig. 6).

High susceptibility

Short-season crops, particularly rice (Fig. 6A) and maize (Fig. 6B), had the highest volatility. The rice and maize CVs reached 29.8% and 33.7%, respectively, across the scenarios. This volatility was attributed to sensitivity to pre-rainy season rainfall variability (May–July), which was projected to increase (Fig. 4) (Khadka et al., 2021b).

Lower susceptibility

Long-season, deeper-rooted crops, namely cassava (Fig. 6C) and sugarcane (Fig. 6D), had comparatively lower yield variability, with CVs peaking at 19.1% and 16.8%, respectively. This difference indicated the higher stability and lower climate risk associated with these crop systems.

Basin-wide and combined economic impacts

Aggregating outputs into a single economic metric (million USD) quantified adaptive capacity at the basin scale.

Baseline output

Under the baseline scenario (Baseline climate/LDD2019), the total agricultural output was estimated at USD 4,506.9 million (Fig. 7A). Rice constituted the largest component, accounting for approximately 50% of the total output.

Climate-only impact

The isolated effect of climate change (Projected climate/LDD2019) caused a basin-wide economic loss of 8.9%.

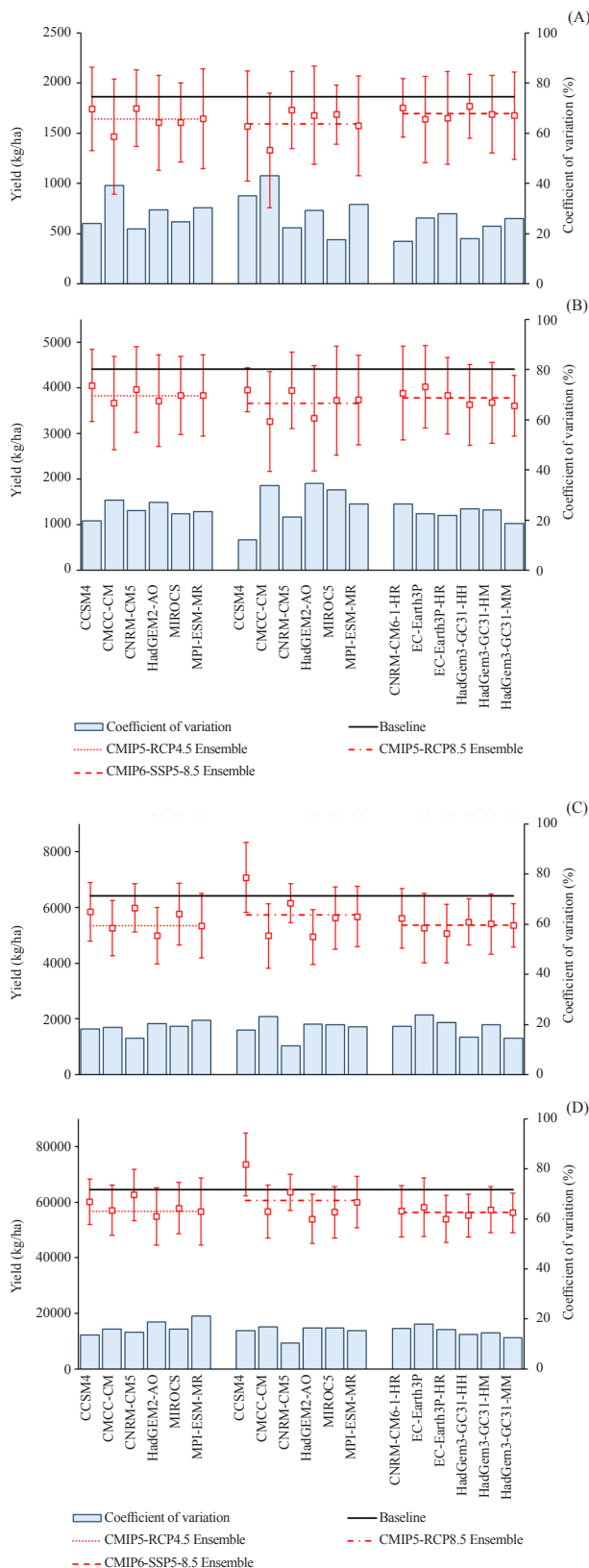


Fig. 6 Yields under baseline climate (1981–2010) (bold line) and projected climate scenarios for: (A) rice; (B) maize; (C) cassava; (D) sugarcane, where individual model results are shown by rectangular points (mean ± SD)

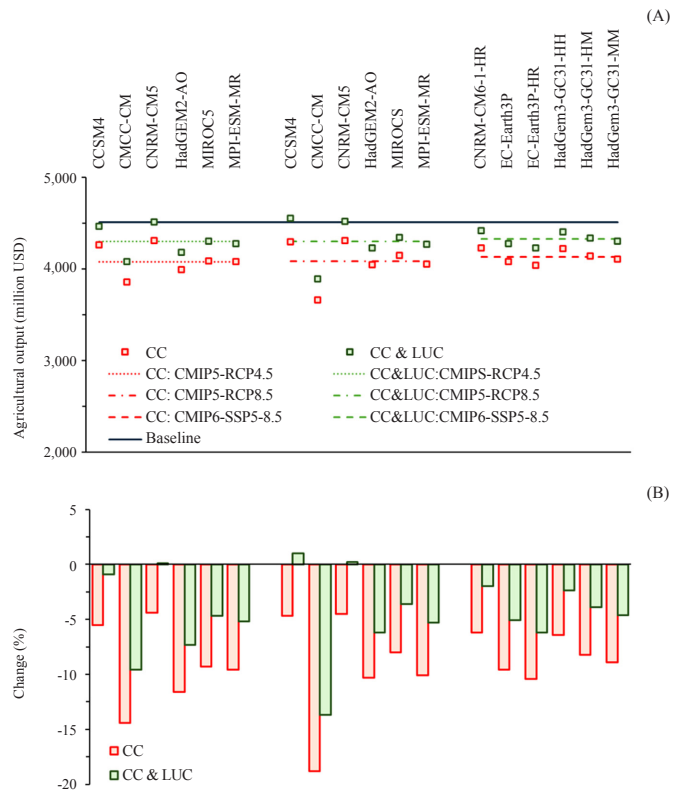


Fig. 7 (A) Basin-level agricultural outputs under baseline climate and projected climate scenarios, where individual model output (rectangular) and multi-model ensemble results (lines) are shown for two impact types: climate change only (CC, in red, using LDD2019 land use) and integrated climate and land use change (CC & LUC, in green, using BAU 2045 land use); (B) percentage of change compared to baseline climate

LUC compensatory effect

The LUC-only scenario (Baseline climate/BAU2045) generated an offsetting economic gain of +4.5% (USD 4,708.7 million).

Net integrated impact

LUC compensation partially mitigated the negative impact of CC. The integrated impact (Projected climate/BAU2045) resulted in a net output reduction of only 4.4%. This result confirmed the potential of strategic land use management as a high-leverage adaptation strategy.

District-level spatial heterogeneity

The district-level assessment revealed that adaptive success and overall vulnerability were highly spatially differentiated, a factor directly influencing localized resource management.

Baseline distribution

Fig. 8A indicates that the high-income districts were predominantly located in upland areas dominated by field

crops and perennial plants, while the low-income areas were characterized by paddy rice in the northeastern lowlands.

Successful mitigation

Successful mitigation was defined as areas where the integrated scenario resulted in a net positive economic change or reduced losses compared to the CC-only scenario. Districts with suitable land and water conditions, such as Sangkha (SKA) and Dan Khun Tod (DKT), demonstrated effective adaptation (Figs. 8 and 9). In SKA, beneficial LUC drove a net output increase of 22.2% under the combined scenario. Similarly, DKT reduced its CC-only loss of 13.1% to a net reduction of 7.2%.

Aggravated vulnerability

Maladaptive land use changes were indicated by areas where net economic loss was intensified under the combined scenario compared to the loss driven by climate change alone. Rice-dominant lowland districts showed heightened susceptibility (Fig. 9), with Kaset Wisai (KSW) experiencing the most severe impact, where combined effects caused a 15.0% reduction in total output. Similarly, Phlaplachai (PPC) recorded an integrated output reduction of 12.3%, which marginally exceeded its CC-only loss of 12.2%, indicating that limited

land-use changes offered no meaningful offset. This disparity illustrated the high risk of promoting generalized adaptation strategies without considering site-specific suitability.

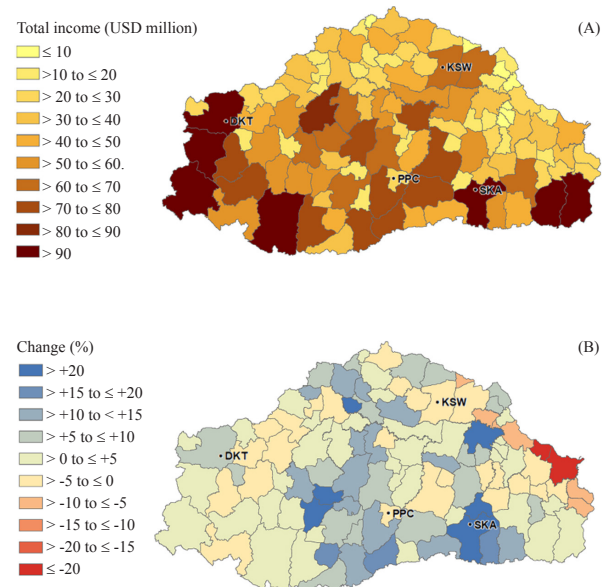


Fig. 8 Spatial distribution of district-level total agricultural outputs (million USD): (A) baseline values under 30 year climate (1981–2010) and LDD2019 land use scenario and (B) corresponding changes under projected BAU2045 land use scenario

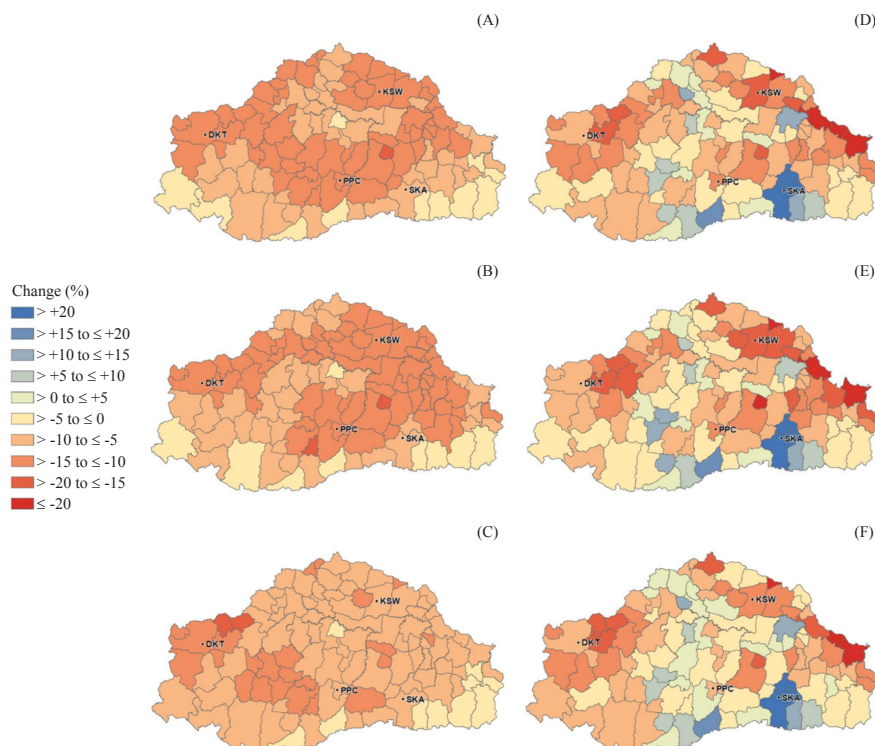


Fig. 9 Agricultural output changes relative to baseline for different climate scenarios: left column, LDD2019 land use and right column, BAU2045 land use: (A) CMIP5-RCP4.5; (B) CMIP5-RCP8.5; (C) CMIP6-SSP5-8.5; (D) CMIP5-RCP4.5; (E) CMIP5-RCP8.5; (F) CMIP6-SSP5-8.5

Discussion

The integrated assessment indicates that while climate change diminishes agricultural output across the Mun River Basin, strategic land use change functions as a compensatory mechanism. Crop conversion represents a central element of regional adaptive capacity, linking physical susceptibility mechanisms to targeted policy recommendations.

Methodological and regional comparisons

Standard climate impact assessments often isolate variables, relying on single-field crop simulations or static land cover assumptions (Babel et al., 2011; Mainuddin et al., 2012). The framework applied in this study differs by integrating DSSAT-LSU spatial simulations with CA-Markov land use modeling. This integration allows the evaluation of concurrent climate and land-use pressures at the basin scale (Wang et al., 2013; Mehdi et al., 2015). The projected 8.9% baseline decline in crop yield aligns with regional studies indicating generalized production constraints from warming temperatures (Das et al., 2020; Debnath et al., 2021). Factoring in land use change, however, yields a net economic loss of 4.4%. This offset demonstrates the buffering capacity of agricultural conversion—a dynamic that is often omitted in standard plot-scale impact studies.

Multi-crop susceptibility and adaptive capacity mechanisms

Agricultural susceptibility depends on the physiological traits of dominant crops. Short-season crops (rice, maize) exhibit substantial yield instability, signaling low adaptive capacity (Abatan et al., 2023). This instability worsens with projected pre-rainy season rainfall declines (Khadka et al., 2021b), which delay planting and induce early-cycle water stress. Conversely, shifting toward cassava and perennial plants enhances adaptive capacity. These long-season and deep-rooted crops possess lower yield variability and better drought tolerance. As a result, adapting the agricultural product mix generates a 4.5% basin-wide economic gain.

Spatial limits of adaptation and policy validation

The efficacy of land-use-driven adaptation depends on local physical suitability. Upland districts, such as SKA and DKT, recorded measurable output increases, confirming that crop

conversion succeeds under suitable land and water conditions. In rice-dominant lowlands (such as KSW), land-use changes—namely land abandonment or maladaptive crop shifts—aggravated economic losses. Generalized crop conversion without regard for flood risk and soil constraints increases vulnerability. This spatial heterogeneity emphasizes the need for site-specific policy and invalidates uniform adaptation approaches.

Limitations and future research directions

The near-future temporal scope of this study (2021–2050) supports immediate local planning (Tingsanchali et al., 2022) but excludes late-century climatic effects. Furthermore, the methodology utilizes a business-as-usual land use scenario. This scenario demonstrates the technical viability of crop conversion but does not account for socio-economic implementation barriers. Future research should integrate socio-economic drivers, conduct formal sensitivity analysis on transition variables, such as crop prices, and quantify ecosystem service trade-offs.

Conclusion

In conclusion, this study integrated the DSSAT-LSU spatial simulation framework with CMIP5/CMIP6 climate projections and CA-Markov land use modeling to quantify economic vulnerability in the Mun River Basin. The analysis demonstrates that strategic land use conversion generates a 4.5% economic offset, reducing the 8.9% climate-driven decline to a net 4.4% loss. While effective, this adaptation depends on local physical conditions; district-level results distinguish areas of successful conversion from those with intensified susceptibility. Therefore, future adaptive planning must prioritize site-specific policy and address implementation barriers.

Conflict of Interest

The authors declare that there are no conflicts of interest.

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