Co-evolution of ecosystem services and land use/ land cover change in the mountains of Eastern China

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Abstract

Land use and land cover (LULC) change, shaped by socio-economic development and climate variability, has profound implications for ecosystem services (ES), particularly in fragile mountain and coastal regions of China. Existing studies of the ES-LULC nexus in China lack systematic review, often short-term and retrospective, with limited use of scenario-based modelling. As a result, the long-term dynamics, vulnerabilities, and future trajectories of socio-ecological systems under interacting socio-economic and climatic drivers remain insufficiently understood.

This dissertation combines a systematic review, long-term empirical analysis, and system dynamics modelling to investigate the co-evolution of LULC and ES in Chinese mountain regions, with Shandong Province as a representative case. 1) The systematic review of 203 articles (2007 – 2024) shows that ES-LULC research in Chinese mountain regions has grown rapidly but remains uneven in scale, methodology, and regional focus. English-language studies tend to operate at broader spatial and temporal scales using biophysical models, with greater attention to regulating services, whereas Chinese studies are concentrated at smaller regional scales, relying mainly on statistical analysis and value transfer methods, and focus more on provisioning services. Overall, long-term time-series analyses, cross-scale comparisons, and scenario-based assessments remain limited, constraining a systematic understanding of ES evolution, trade-offs, and feedbacks. 2) Using long-term data (1950 – 2022) and causality testing in Shandong Province, the study reveals that urban expansion and economic growth significantly drove the increase of construction land, intensifying trade-offs between provisioning services such as food production and regulating services such as carbon storage and water regulation. Wetland loss and precipitation decline exacerbated negative feedbacks, accelerating vegetation degradation and drought risks. Overall, system connectivity declined markedly after 1980, resilience weakened, and the socio-ecological system showed a tendency toward functional disturbance and potential reorganization. 3) System dynamics simulations (2020 – 2100) reveal strong nonlinearity and path dependency in ES-LULC trajectories. Under extreme warming and drought, agricultural, forest,

and water systems risk synchronous collapse by mid-century, signalling the approach of socio-ecological tipping points. Adaptive management can delay destabilisation but generates unavoidable trade-offs—for example, between food and water or carbon and water. Socio-economic pathways further amplify these dynamics, with sustainability-oriented futures slowing risk accumulation and fossil-fuelled trajectories accelerating systemic decline.

Policy insights include strengthening farmland protection and sustainable management to secure food and carbon storage; scaling up water-saving measures to enhance resilience under climate extremes; conserving wetlands to buffer rainfall decline and drought; and carefully designing afforestation strategies to balance water–carbon trade-offs. Prioritising sustainability-oriented socio-economic pathways offers the most robust option for maintaining long-term system stability.

This dissertation contributes academically by advancing understanding of ES-LULC co-evolution in Chinese mountain and regional systems, methodologically by integrating causality testing with system dynamics into a transferable framework, and practically by providing evidence-based insights for land–water–carbon governance in Shandong and other regions facing similar pressures.

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Acknowledgements

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Author's Declaration

I declare that, except where explicit reference is made to the contribution of others (e.g. publicly available datasets), this dissertation is entirely the result of my own work and has not been submitted for any other degree at the University of Glasgow or any other institution.

Chapters 2, 3, and 4 are presented in the form of an Alternative Format Thesis, in accordance with the University's Code of Practice. The texts, figures, and tables in these chapters are largely identical to the versions that have been published or submitted, with additional details incorporated as requested by the thesis examiners. To ensure consistency throughout the thesis, the numbering and formatting of tables, figures, appendices, and references have been standardised. Supplementary materials from these papers (e.g. data sources) have been relocated to the Appendices.

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List of Acronyms and Abbreviations

ABM	Agent-Based Model
B/Tra	Bundle/Trade-off
CASA	Carnegie–Ames–Stanford Approach model
CES	Cultural Ecosystem Services
CICES	Common International Classification of Ecosystem Services
CNKI	China National Knowledge Infrastructure
EKC	Environmental Kuznets Curve
ES	Ecosystem services
ES-LULC	Ecosystem services-Land use/ land cover
ESP	Ecological Security Pattern
GDP	Gross Domestic Product
GIS	Geographic Information Systems
InVEST	Integrated Valuation of Ecosystem Services and Tradeoffs
IPBES	Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services
IPCC	Intergovernmental Panel on Climate Change
LU	Land use
LULC	Land use/ land cover
MA	Millennium Ecosystem Assessment
MES	Mountain ecosystem services
NPP	Net Primary Productivity

RUSLE	Revised Universal Soil Loss Equation
SDGs	Sustainable Development Goals
SDM	Social dynamic model
SES	Social ecological systems
SO	Spatial Overlay
sPCA	Sequential Principal Component Analysis
SSP	Shared Socioeconomic Pathway
Sta	Statistical analysis
SWAT	Soil and Water Assessment Tool
TEEB	The Economics of Ecosystems and Biodiversity
UN	United Nations
VTM	Value Transfer Method

Chapter 1 Introduction

1.1 Background

Although mountain regions comprise only 27% of the Earth's terrestrial surface, they underpin the well-being of nearly half of the global population through the provision of critical ecosystem services (ES), including fresh water, raw materials and cultural benefits (Alfthan et al., 2018; Schirpke et al., 2019). However, mountain ecosystems, as one of the world's most endangered and sensitive ecosystems, are undergoing profound environmental and socio-economic transformations (Lavorel et al., 2023), the consequences of which are manifested in polarized land use/ land cover (LULC) patterns: on the one hand, there is widespread farmland abandonment(Dax et al., 2021), natural rewilding (Carroll & Noss, 2021), and state-led ecological restoration programs such as the 'Grain for Green Program' in China (Fan & Xiao, 2020), while on the other hand, rapid urbanization (Anees et al., 2022), tourism expansion (Iversen et al., 2024), and rural revitalization efforts (Li et al., 2022) are reshaping mountain landscapes. These divergent trajectories reflect growing tensions between ecosystem service supply and socio-economic demand, particularly in areas where land system transitions are accelerating without adequate ecological assessments.

In response to these transformations, scholars have emphasized the need to integrate ES assessments with mountain LULC analysis in order to better understand their interactions and to inform sustainable management strategies (Fu et al., 2015a; Vigl et al., 2017). Ecosystem services are defined as the value and benefits that ecosystems contribute to human well-being (CICES, 2011; Costanza et al., 1997; MEA, 2005; TEEB, 2010). In 2005, the Millennium Ecosystem Assessment (MA) proposed a widely adopted framework to categorize services into four types: provisioning services (e.g., food or energy output), regulating services (e.g., regulating floods, droughts, land degradation, and disease), supporting services (e.g., soil formation and nutrient cycling), and cultural services (e.g., non-material benefits such as recreation, religion) (MEA, 2005). Since then, several derivative frameworks have emerged to refine or expand upon the MA structure--e.g., the Economics of Ecosystems and

Biodiversity (TEEB, 2010) initiative aims to assess the economic benefits of biodiversity, and the framework Common International Classification of Ecosystem Services (CICES, 2011), used in the EU Mapping and Assessment of Ecosystems and their Services (MAES, 2013) process for mapping ecosystem services at the European scale. This study adopts the MA framework due to its global applicability, conceptual completeness, and strong compatibility with the socio-ecological complexity of Chinese mountain regions. Its four-tier classification enables the inclusion of both material and non-material services, making it suitable for integrated assessments in data-limited, multi-functional mountainous landscapes. LULC refer respectively to human-induced land uses (e.g., agriculture, urban expansion, infrastructure) and the biophysical attributes of the Earth's surface natural or semi-natural physical cover types (e.g., vegetation, water, barren land) (Chowdhury et al., 2020; Nedd et al., 2021). LULC change is one of the primary drivers of ecosystem service variation, especially in mountainous regions where socio-economic pressures and ecological fragility intersect (Belay et al., 2022; Fang et al., 2022a). In this context, co-evolution is defined as a reciprocal, dynamic process in which ecosystem services and land use mutually shape each other's trajectories over time through feedback mechanisms and adaptive responses (Dearing et al., 2010). Unlike unidirectional cause–effect models, the co-evolutionary perspective emphasizes non-linearity, time-lag effects, and system memory, making it particularly suitable for understanding long-term social–ecological interactions in mountain systems.

1.2 Research progress, gaps and novelty

Over the past decades, a number of literature reviews have advanced our understanding of mountain ES. Mengist et al. (2020) synthesized methodological advances and research gaps in mountain ES studies; Pătru-Stupariu et al. (2020) highlighted the translational challenges from ES theory to LULC practice; Liu et al. (2022) explored the interactions among ES, LULC, and human well-being from a broader systems perspective. Although previous reviews have significantly contributed to ES, most have focused on general frameworks of global view, with limited consideration of the coupled dynamics between mountain ES and LULC in the Chinese context. To date, no systematic review has specifically targeted mountain regions of China, leaving a gap in understanding the unique socio-ecological processes, methodological trends, and indicator usage in these landscapes. This omission has limited the identification of methodological trends, indicator usage, and critical knowledge blind spots, thus constraining the strategic alignment of ES research with regional policy needs. A context-specific synthesis is urgently needed to reveal the temporal and spatial patterns of research foci, clarify evolving methodological choices, and inform future work.

Beyond literature syntheses, empirical investigations have proliferated to capture how LULC dynamics affect the ES provision, spatial heterogeneity, and trade-offs of mountain ES (Belay et al., 2022; Fang et al., 2022; Wang et al., 2018). Methodologically, studies often adopt statistical analysis and spatial overlay to quantify ES-LULC relationships (Shao et al., 2020), apply biophysical models (e.g., InVEST model) to simulate ecological processes (Li & Cai, 2022; Pan et al., 2024), and employ scenario-based approaches to explore future spatio-temporal dynamics (Hua et al., 2024; Zhang et al., 2025). Despite these contributions, three key limitations persist. First, the majority of existing studies rely on short-term snapshots and fail to systematically capture the long-term co-evolutionary dynamics between ES and LULC, thereby overlooking non-linear interactions and latent feedback loops (Pan et al., 2024; Yuan et al., 2024). Second, while widely used, most biophysical models such as InVEST are grounded in static input–output structures and are not designed to simulate system feedbacks, temporal lags, or tipping points. These omissions limit our capacity to anticipate and manage complex socio-ecological changes. Third, in the Chinese context, although ES modeling has progressed, most studies remain descriptive or correlation-based, lacking integrated dynamic system analysis.

These limitations constrain their capacity to inform adaptive policy design and long-term sustainability planning. These gaps hinder our ability to understand the functioning of mountain systems and compromise the scientific basis for ecological restoration, LULC governance, and resource management. Under the dual pressures of climate change and socio-economic transition, the failure to identify critical thresholds or regime shifts may lead to irreversible ecosystem degradation, undermining the provision of ecosystem services and human well-being (Hossain et al., 2017).

To address these gaps, this thesis makes three novel and first-of-their-kind contributions:

(i) The first systematic review focusing exclusively on mountain ES-LULC research in China, revealing spatial–temporal trends, methodological divergences, and unaddressed gaps;
(ii) The first empirical analysis to quantify causal relationships and co-evolutionary dynamics between ES and LULC in a representative mountainous region of eastern China; and
(iii) The first development and simulation of a region-specific system dynamics model for Shandong Province's integrated socio-ecological system, enabling scenario-based assessment of long-term trajectories, trade-offs, and synergies.

Together, these first-of-their-kind studies not only advance methodological capacity but also directly address long-standing gaps in understanding ES-LULC dynamics, providing actionable insights for sustainable land governance in ecologically sensitive mountain regions.

1.3 Research aim and questions

The overall goal of this thesis is to advance the understanding of the coupled dynamics between mountain ES and LULC in China, and to develop integrated modelling approaches that can inform sustainable land governance in ecologically sensitive mountain regions. To achieve this, this thesis integrates a multi-method investigation into the coupled dynamics between mountain ES and LULC in China. It begins with a comprehensive synthesis of existing literature to clarify the evolution of concepts, methods, and spatial–temporal patterns in ES-LULC research. Building on these insights, it then empirically quantifies the co-evolutionary relationships between mountain ES and LULC of eastern China, and further develops a region-specific system dynamics model to simulate long-term trajectories, identify potential tipping points, assess trade-offs and synergies under multiple future scenarios. The modelling and analysis contribute to achieving synergies and managing trade-offs for maintaining a safe operating space in sustainability science decision-making processes. Through this integrated approach, the thesis seeks to bridge the gap between static assessments and dynamic system understanding, and to inform sustainable land management in ecologically sensitive mountain regions.

To achieve this overall goal, the following research questions (RQs) will be answered and understood:

RQ1: What are the major spatial–temporal hotspots and trends, methodological advances, and research gaps in ES-LULC studies in China's mountainous regions?

RQ2: How have ES-LULC changed over time in a representative mountainous region of eastern China?

RQ3: What are the dominant co-evolutionary patterns in ES-LULC, and how do trade-offs and feedback manifest over time?

RQ4: How can system dynamics modelling be used to simulate future co-evolutionary trajectories of ES-LULC under multiple scenarios, identify potential tipping points, and define the safe operating space for sustainable land governance in mountainous regions?

1.4 Scientific and policy contributions

This research makes distinctive contributions to both science and policy. Scientifically, it advances understanding of socio-ecological dynamics by (i) systematically synthesizing mountain ES-LULC studies in China and identifying major methodological and thematic gaps, (ii) providing empirical evidence from Shandong that reveals long-term feedbacks between urbanization, wetland decline, and ecosystem regulation, and (iii) developing a system dynamics model that integrates climate, demographic, and LULC drivers to simulate coupled trajectories, trade-offs, and potential tipping risks. By explicitly linking LULC scenarios to ecosystem tipping dynamics and policy thresholds, the model establishes a scalable and transferable platform for strategic planning. Collectively, these contributions establish a multi-method framework that strengthens both explanatory and predictive capacity in socio-ecological research.

In terms of policy relevance, the findings are grounded in China's rapid LULC transitions and provide quantitative evidence for spatial governance instruments such as ecological redlines, provincial LULC zoning, and integrated land–water–carbon strategies. The analysis highlights risks from unchecked urbanization and wetland degradation, while also demonstrating the potential benefits of farmland protection, targeted afforestation, water-saving technologies, and dual carbon control. At the global level, the transferable modelling framework contributes to anticipatory governance in other climate-sensitive mountain and coastal regions, aligning with international agendas including the Sustainable Development Goals (SDG 15, SDG 13), the Kunming–Montreal Global Biodiversity Framework, and the Paris Agreement.

1.5 Study area

Shandong Province (Figure 1.5-1), situated along the eastern coast of China, serves as an exemplary case for examining the co-evolution of LULC and ES within a complex socio-ecological framework. Spanning approximately 157,900 km², Shandong is the second most populous province in China, home to over 100 million residents, and ranks third in national GDP, with a gross regional product of 4.67 trillion RMB in 2023 (*China Statistical Yearbook*, 2023). The province leads the country in both vegetable and aquatic product output—producing 92 million tons and 9.14 million tons respectively in 2023—making it central to China's food security and a major contributor to regional provisioning services that extend beyond national borders.

Climatically, Shandong has a warm temperate monsoonal climate, with average annual temperatures ranging from 11°C to 14°C and annual precipitation between 600 mm and 750 mm. More than half of its rainfall is concentrated during the summer months, while spring and autumn are prone to droughts (Shandong Statistical Yearbook, 1983–2022). These conditions accentuate the seasonal variability of water availability and place additional stress on both natural and managed ecosystems. The province also has one of the longest coastlines in China (approx. 3345 km), further contributing to its ecological complexity and socio-economic importance.

Over the past four decades, Shandong has undergone rapid LULC transformation. Its urbanization rate increased from 13% in 1985 to 66% in 2023 (Ren et al., 2023). This expansion—driven by industrialization, rural–urban migration, and major infrastructure investment—has led to extensive encroachment upon agricultural lands, wetlands, and forest areas. Policy shifts, including farmland protection and reforestation campaigns, have simultaneously reshaped LU trajectories, triggering nonlinear impacts on ecosystem structure and function (Fan & Xiao, 2020). These dynamics have generated intensified land fragmentation, biodiversity loss, and trade-offs among provisioning, regulating, and supporting services.

From a research perspective, Shandong provides a highly suitable context for modelling socio-ecological interactions. It represents a typical mountainous–coastal hybrid system in China, and also reflects broader transitions in the Global South. Furthermore, Shandong benefits from high statistical data accessibility and a relatively transparent governance environment. Key data for this study—spanning LU, ES, meteorological, demographic, and economic indicators—were collected from a range of authoritative sources, including the Shandong Statistical Yearbook, China Statistical Yearbook, National Climatic Data Center (NCDC), Shandong Environmental Bulletin, China Meteorological Disaster Statistical Yearbook, and China Environmental Statistical Yearbook. The research team's prior experience and long-term familiarity with provincial data sources facilitated communication with local bureaus and ensured robust data curation and validation.

In light of these ecological, economic, and institutional characteristics, Shandong Province emerges as an ideal laboratory for testing system dynamics models of land–ecosystem interactions. Its data richness, diverse socio-environmental gradients, and policy relevance position it not only as a representative case for China, but also as a transferable model for investigating safe operating spaces and adaptive governance in other rapidly urbanizing, agriculturally intensive regions worldwide.

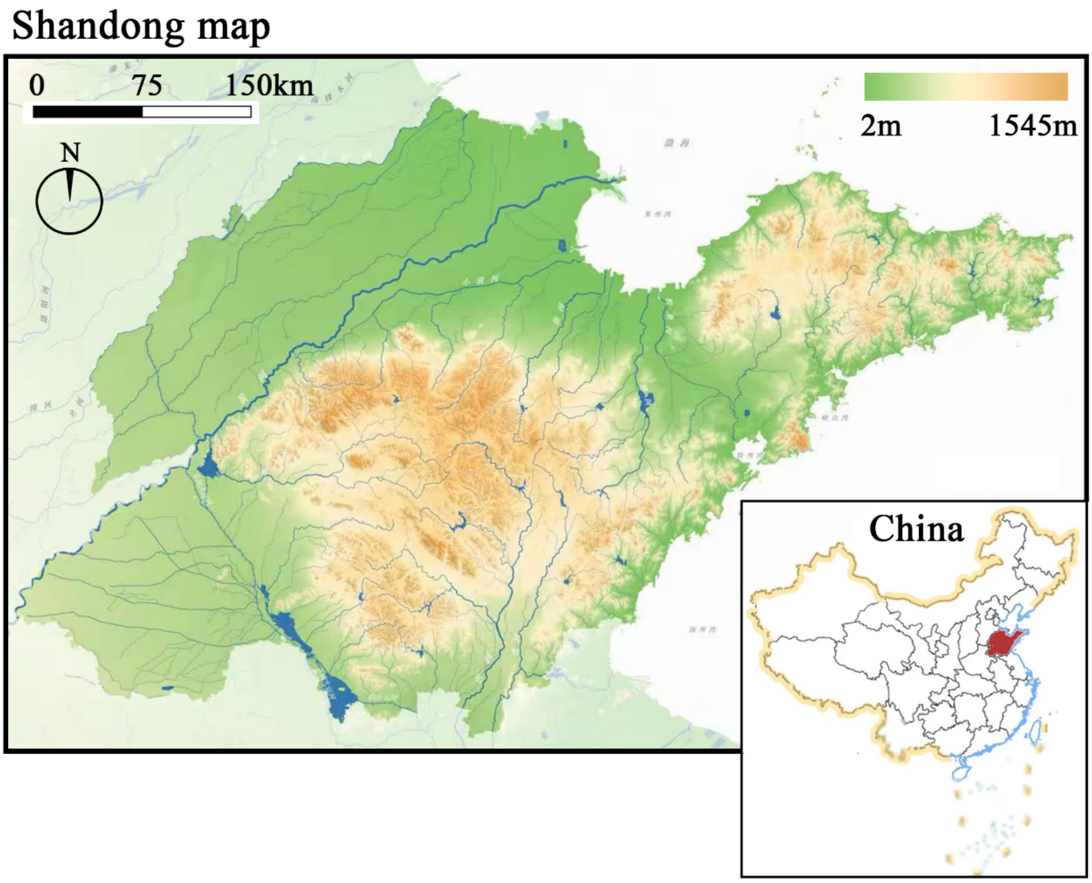


Figure 1.5-1 The location of Shandong province of China.

1.6 Thesis structure

This thesis comprises three interlinked empirical studies that collectively examine the co-evolutionary dynamics of ES-LULC in mountainous regions of China, with a particular focus on Shandong Province. The research follows a stepwise structure that progresses from knowledge synthesis and mechanism identification to dynamic simulation and policy-oriented exploration (Figure 1.6-1).

Chapter 2 presents a systematic literature review of 146 peer-reviewed articles published between 2007 and 2022, including 66 in Chinese and 80 in English. Chinese-language studies were retrieved from CNKI, while English-language studies were sourced from Scopus and Web of Science. Following the ROSES protocol, the review assesses ES-LULC studies in Chinese mountain regions with respect to spatial scale, methodological orientation, and temporal coverage. The results reveal widespread limitations, including the absence of dynamic modelling, inadequate integration across spatial scales, and a lack of forward-looking scenario analysis. These insights provide a conceptual foundation for the subsequent empirical modelling and inform the core research questions of the thesis.

Chapter 3 investigates the feedback relationships among land use, ecosystem services, and socio-economic factors in Shandong Province using time-series data from 1950 to 2020. Data were primarily drawn from the Shandong Statistical Yearbook, Shandong Environmental Status Bulletin, China Meteorological Disaster Yearbook, and China Environmental Statistical Yearbook, with meteorological data obtained from the National Climatic Data Center. To uncover dynamic interactions, the analysis first applies Granger causality testing to identify lead–lag relationships among key variables (e.g., cropland area, water bodies, carbon storage, and GDP), clarifying temporal drivers of change. Second, the Environmental Kuznets Curve (EKC) model is used to examine potential non-linearities between economic growth and ecosystem service trends, such as degradation–recovery thresholds. Third, sequential principal component analysis (sPCA) is employed to reduce dimensionality and extract dominant modes of system co-evolution. Collectively, these methods reveal critical feedback mechanisms, leverage points, and early warning signals of transformation, which provide empirical input for the construction of the system dynamics model in the next chapter.

Chapter 4 builds on these empirical findings to develop a system dynamics (SD) model that simulates long-term ES-LULC trajectories under multiple climate, demographic, and LULC policy scenarios. The model encompasses seven land use categories and seven ecosystem service types and follows a structured modelling process that includes causal loop diagram construction, stock–flow architecture, historical calibration (1995 − 2020), and sensitivity testing. Scenario design incorporates diverse socio-environmental pathways, including afforestation, cropland protection, water-saving strategies, and urban containment, overlaid with climate projections ranging from 1.5 to 5.7°C temperature increases and − 70% to + 50% precipitation variation. Simulation results identify potential tipping points and safe operating thresholds for regional ES-LULC systems, offering insights for adaptive governance under compounded environmental pressures. Simulation results reveal both potential tipping points and the boundaries of a safe operating space within which ecosystem services can be sustained under compounded environmental stress. By mapping system responses across diverse futures, the model provides a quantitative basis for evaluating trade-offs, guiding adaptive land governance, and anticipating policy-relevant thresholds. These findings set the stage for the synthesis and broader reflections in Chapter 5.

Chapter 5 synthesizes the findings from the three studies, discusses their relevance for integrated land–ecosystem policy design, and reflects on the theoretical and practical implications of modelling ES-LULC co-evolution in mountainous regions. It also considers key limitations and outlines future directions for advancing social-ecological systems modelling and sustainability planning at regional scales.

Papers	Methods	Research Aims	Steps in SD modelling	Output
1st	Search in Chinese and English article in China's research ROSES forms	***Systematic review: ES and LU change research in the mountain regions of China***	Research gap Future direction	Systematic review Trends & gaps Future directions
2nd	Granger causality test Sequential PCA EKC model	***Co-evolution and Inter-linkages between ES and LU***	Model formulation (Causal loop diagram)	Trend analysis Causal feedback model Key drivers Connectivity decline
3rd	System dynamic modelling Scenarios	***Exploring dynamics of social-ecological systems***	Parameter estimation Validation Sensitivity test Simulation	SD model Multi-scenario simulation Trade-offs & synergies Tipping points Policy priorities

Figure 1.6-1 The methodological flow diagram of the thesis.
It shows links among papers, research questions, methods, steps, outputs for 3 papers.

Chapter 2 Ecosystem services and land use change research in the mountain regions of China: A systematic review

Land use/ land cover (LULC) change driven by anthropogenic activities has increasingly threatened mountain ecosystem services (MESs), yet a systematic understanding of this issue in the mountains of China remains limited. This study aims to synthesize the current state of knowledge on Chinese MES & LULC research, identify key research trends, and inform future research and policy directions in Chinese mountains. We systematically reviewed 203 peer-reviewed articles published between 2007 and 2024, including 82 in Chinese and 121 in English. Although most studies (79%) are historically oriented, the attention to future scenario-based assessments is growing rapidly. English-language literature tends to adopt broader regional scales and longer time duration, focusing on ecological processes by biophysical models. In contrast, Chinese studies primarily operate at the smaller regional or local scale and rely heavily on statistical analysis and mapping, especially based on value transfer method for ES valuation. Despite growing academic attention since 2018, major research gaps remain: The lack of a unified multi-scale framework has led to fragmented and poorly comparable ES assessments; the use of time-series approaches or studies with over three temporal observations remain limited (33%), constraining the analysis of MES & LULC evolution, trade-offs, and system feedbacks; and the lack of futural scenario-based evolution under different land policies and extreme environmental changes. Our findings contribute to the scientific guidance for the implementation of future ecological restoration planning in China and other mountainous regions.

2.1 Introduction

Mountain ecosystems provide a diverse array of ecosystem services (ESs) to people living within their foothills (over 15% of the global population) and the adjacent lowlands (Locatelli et al., 2017). These services (e.g., food, water, medicine) offer numerous benefits to human well-being from the ecosystem, social livelihood, and social-economic view (MEA, 2005; TEEB, 2010; CICES, 2011; IPBES, 2019). In addition, mountain ecosystems regulate climate, air quality, and water flow, benefiting downstream populations (Viviroli et al., 2020). While mountain ecosystems are critical for human development and the global ecosystem health, the provision of these ecosystems is highly dependent on land use/land cover change (LULC).

LULC itself is shaped by long-term interactions between humans and nature (Verburg et al., 2013). More than 70% of the planet's land surface has experienced some form of anthropogenic change (Luyssaert et al., 2014), and the anthropogenic LULC has disrupted planetary-scale biophysical (e.g., soil formation) and biogeochemical processes (e.g., carbon storage) (Winkler et al., 2021; Riano Sanchez et al., 2024). Mountain ecosystems, however, are 2–3 times more vulnerable to LULC and climate change than lowland regions, due to their steep ecological gradients and tightly coupled socio-ecological systems (IPBES, 2019; Immerzeel et al., 2020; Pepin et al., 2022). LULC-driven vulnerability degrades mountain ESs, with losses cascading to lowlands (e.g., water supply, climate disaster). Regarding the loss of ES values globally, LULC change (LULCC) and land degradation affect ecosystem health, directly affecting half of humanity, and led to a loss of about \$40 trillion a year of ESs, which is almost half of global GDP (\$93 trillion) in 2021 (Vander et al., 2022). China has experienced Earth's fastest LULC transitions Since 1990, with its mountains serving as focal points for socio-ecological tensions (Wang et al., 2018). These dynamics have spurred growing interest in LULC-ES interactions, necessitating systematic review to guide future research and advance global mountain studies.

China is a mountainous country, with mountains, plateaus, and hills accounting for 67 % of land area and 18.4 % of the world's mountainous area (Deng et al., 2015). These regions are home to the largest concentration of poverty in China, with 310 million people dependent on mountain ecosystems (Wen, 2023). China's mountain regions have experienced profound LULC transformations, driven by population growth, urbanization, and policy interventions, which have significantly reshaped its ESs, creating a complex interplay of ecological and socioeconomic trade-offs. (Marks, 2017). Population growth after the founding of New China in 1949 increased the demand for livelihoods and necessitated the reclamation of forest and unused land in mountainous areas. Since 1990, urbanization and ecological restoration initiatives have profoundly transformed LULC patterns in China's mountainous regions. The expansion of construction land, driven by urbanization, has encroached upon farmland, grassland and barren land, resulting in landscape fragmentation and a significant decline in total ES values, including reduced carbon storage and degraded habitats (Yang, 2021; Zhang et al., 2022). In contrast, the conversion of farmland into ecological land (e.g., forests and grasslands) under initiatives like the Grain for Green Project has supported critical ESs, including soil and water conservation and carbon sequestration(Cheng et al. 2024; Wang et al., 2017). These contrasting trends highlight the complex trade-offs between economic development and ecological sustainability in China's rapidly changing mountainous regions (Deng et al., 2021).

Therefore, linking MESs with LULC research, and clarifying the impact (Fan & Xiao, 2020), synergistic trade-offs (Shi et al., 2021) can effectively reveal the interactions between human and natural systems, improve our understanding of ES processes and mechanisms, and facilitate the formulation and implementation of land use planning and ecological protection policies. It is also of great scientific importance in promoting regional sustainable development (Gong et al., 2021).

Most studies to date have focused on regional case studies of LULC & ESs (Wang et al., 2023; Zhang et al., 2022), leaving systematic reviews of the broader body of research insufficient. One major gap is the inadequate attention to the unique characteristics of mountain ecosystems. While many reviews aggregate data from a range of global landscapes (Liu et al., 2022; Haque and Sharifi, 2024), they often fail to address specific mountain attributes (e.g., vertical gradients, vulnerability thresholds, and the spatial variation of population-resource conflicts). Furthermore, many existing reviews primarily adopt a global perspective, discussing ESs (Evans et al., 2022; Haque and Sharifi, 2024), LULC (Gomes et al., 2021; Roy et al., 2022), and their connections to human well-being (Liu et al., 2022), but overlook China's specific context. As a result, there is a lack of systematic reviews at the national scale, which limits the ability to effectively summarize and guide future research on China's mountain ecosystems (Jiang et al., 2021). Additionally, global reviews tend to rely heavily on English-language sources, disregarding valuable Chinese literature, which can lead to biased conclusions(Canedoli et al., 2024; Jiang et al., 2021). Finally, the lessons from China's mountainous regions for global mountain sustainability have not been systematically summarized, making it challenging to align with international agendas such as the IPBES and SDGs (Colglazier, 2015; IPBES, 2019).

Therefore, this study aims at providing a first understanding of the research trend and hotspot, approach, and help subsequent researchers finding research gaps and directions for Chinese mountainous areas. We carried out a state-of- the- art quantitative analysis using a systematic literature review of English and Chinese peer-reviewed articles published from 2007 to 2024. The review focused on the following three main objectives within the context of ES and LULC research in the mountain regions of China:

1. To understand research hotspots and research trends of Chinese MESs & LULC across time and space;

2. To document the evidence (such as concepts, models, and data) based on Chinese MESs and LULC research;

3. To identify key research gaps and opportunities, and to provide further research directions for future sustainability of mountain ecosystems research.

The findings of this study can provide useful information on the overall status of MESs & LULC research in the Chinese context and the most common gaps observed. In addition, the study can help researchers identify the scientific progress; the challenges researchers encounter and the gaps that require further research efforts.

2.2 Methodology

2.2.1 Search protocol and selection approach

A systematic review aims to provide a comprehensive, unbiased synthesis of evidence on a clearly defined topic by using critical methods to identify, evaluate, and summarize relevant studies (Hossain et al., 2023; Tricco et al., 2011). It adheres to the general principle of summarizing the knowledge from a body of literature, attempts to uncover “all” of the evidence within a specific time frame and source of research and focuses on research that reports data rather than concepts or theory (Basak et al., 2021). This review adopted the MEA (2005) classification system to ensure consistency across the literature analysed. However, this may limit alignment with recent conceptual advances, and recommend that future reviews adopt updated frameworks such as IPBES (2019) or CICES (2011) to better reflect current understandings of ES types.

2.2.1.1 Identification of data range

To be comprehensive and incorporate as many studies as possible, this systematic review screened literature published in both Chinese and English. This systematic review covered publications from 2007 to 2024 (first research in this field), conducted between November 2021 and June 2025. The English-language publications search were conducted in Scopus and Web of Science using topic-based queries (“Ecosystem service*”), (Mountain* OR Hill*), (“Land use change” OR Land cover* OR Land use* OR LULC OR Land), (China, OR Chinese), and language should be in English. Scopus and Web of Science were selected for their comprehensive indexing of high-quality, peer-reviewed journals in English language and their wide acceptance as authoritative sources for academic research. There are 771 articles found in total, with 239 articles from Scopus and 532 from Web of Science.

For Chinese-language publications, equivalent search terms were applied using Chinese characters in the China National Knowledge Infrastructure (CNKI) database between June 2022 to June 2025. The keywords included “生态系统服务”, (“山*”

OR “*丘陵” OR “*梯田”), (“土地利用变化” OR “土地利用” * OR “土地覆盖” * OR “土地 “) and “中国”. CNKI was selected due to its extensive coverage of Chinese academic journals and its recognized role as the primary repository of peer-reviewed Chinese-language literature. From this screening, 187 articles were retrieved.

2.2.1.2 Reduce the duplication and non-peer-reviewed articles

After that, this study reduced the duplication of these Chinese and English-language articles respectively, and removed the non-peer-reviewed articles (e.g., grey literature, conference papers, book chapters, and editorial letters, as well as documents not published in either Chinese or English). A total of 514 English-language article, and 214 Chinese-language articles were included in the selection process.

2.2.1.3 Title and abstract filtration

After deduplication and peer-review filtering, an eligibility screening was conducted using Zotero software. These articles were screened based on their titles, abstracts and keywords If these sections did not provide sufficient information to determine eligibility, the methods and results sections were further examined. Four criteria were applied to assess relevance: (1) at least one clearly defined ecosystem type was studied; (2) at least one clearly defined ES type was assessed; (3) the study area contains at least part of mountains in China and has research results for mountains of China; (4) include studies on LULC (spatial heterogeneity, LULC change, etc.). Articles that were inaccessible, or conference abstracts behind paywalls or not publicly available, were also excluded.

2.2.1.4 Screening and reviewing papers

Full-text review was conducted using ROSES forms (Haddaway et al., 2018), compiled in Excel. ROSES is a systematic review reporting standard widely used in environmental management studies (https://www.roses-reporting.com/). During this process, the four eligibility criteria were repeatedly applied, and eligible articles were compiled into a structured table (Table 6.1-1). The framework for content analysis was developed by integrating the ROSES checklist with specific research questions. It was structured into a set of categories and key elements for systematic evaluation, including temporal and spatial scale analysis, ES types and methods, LULC approaches, and the modes of assessment, research directions and opportunities. A total of 121 English-language articles and 82 Chinese-language articles were included in the final dataset (Figure 2.2-1).

Figure 2.2-1 Systematic literature review's study selection of literature using inclusion and exclusion criteria in English-language articles (left) and Chinese-language articles (right).

2.2.2 Quantitative and qualitative data analysis

The reviewed articles were sorted to filter full-text information describing the spatial geographic distribution, temporal scales (historical, present, future, cross-scale), temporal scale hotspots (study duration & time interval) (Mengist et al., 2020) and scale hotspots for spatiotemporal studies (study duration & spatial extent) (Estes et al., 2018), ESs and their types (provisioning, regulating, supporting and cultural) (MEA, 2005; IPBES, 2019), the relationship between LULC and ESs, the research methods, models and mode of analysis (Table S1) (Basak et al., 2021). We carried out data management and analysis using Excel tools, and the statistics were plotted through the software - Origin 2018.

2.2.2.1 Spatial scale and temporal scale analysis

The first type of data includes the general nature of the study, which was divided into the spatial scale and temporal scale analysis. The spatial scale studies included the map of study sites research sites (Figure 2.3-1) as well as the spatial coverage of the study (Figure 2.3-2) between 2007 to 2024. The spatial distribution of study sites was analysed using hotspot maps, separately for Chinese and English-language articles at the provincial level in China, using Excel's mapping tools to visualize research intensity. The locations of institutions were manually recorded to analyse spatial associations with study areas, supporting the textual analysis. The spatial coverage was categorised in the form of either regional, local or patch scale. The national scale was not mentioned because the screened articles lacked studies conducted at the national studies. The regional scale includes studies of multiple sites in China and has a scale of 10^4-10^6 km^2. The local scale will be limited to studies of specific areas or cities with a scale of 10^3-10^4 km^2, such as the study of Beijing (Chen et al., 2020). Most of the studies on the patch scale will address smaller scale explorations such as villages or parks.

Regarding the temporal scale review, this study reveals the temporal directions in Chinese and English-language articles (Figure 2.3-3), as well as interval-duration time relationships and spatiotemporal research hotspots (Figure 2.3- 4). Temporal directions refer to studies that address historical (using data collected more than three years prior to the publication date of the article), current (using data collected within three years prior to publication), historical and futural (simulate or project futural LULC or ESs by historical data) will be plotted by bar graphs. The interval-duration time relationships and spatiotemporal research hotspots were developed using Kernel Density maps. These maps analyze two key relationships: (1) the total study duration and the time sampling interval, visualized in Figure 2.3-4 (a, c) to show the sampling density of time evolution; and (2) the spatial coverage and study duration, visualized in Figure 2.3-4 (b, d) to identify spatiotemporal research hotspots.

2.2.2.2 Identify the types of ESs

The second data type focused on identifying the types of ESs mentioned in the literature (Figure 2.3-9). Articles within the criteria will have the term ESs present in the keywords and in the results of each study. Four major types of ESs (Provisioning, regulating, supporting, and culturing) were identified (MEA, 2005), as this classification remains the most widely used in the reviewed literature despite the emergence of newer frameworks such as CICES or IPBES (CICES, 2011; IPBES, 2019). The frequency of research on each type of ESs was counted, and the differences between Chinese and English papers were compared to identify research hotspots and cold spots. By integrating spatial and temporal hotspots, this study identifies current gaps in research across time and space, providing guidance for selecting appropriate spatiotemporal scales in future studies.

2.2.2.3 Relationships Between Qualitative Classifications

The third type of data is related to the strength of the relationship between the different qualitative classifications, i.e., the focus of the study, ES types, ES models, and the mode of analysis for ES and LULC (Figure 2.3-10). To visualize the correlations among key dimensions of the reviewed articles, this research employed Alluvial Diagrams, constructed using the rawgraphs.io platform. The four categories of different combinations -focus (e.g., ecological, social-ecological, social-economic), ES types (different ES groups), models (e.g., Bio-physical model, InVEST model, value transfer method), and modes of analysis (e.g., statistical analysis, scenario simulation, spatial overlay, bundle/trade-off analysis, ecological security pattern) – were summarized in a structured table based on a systematic literature review (Basak et al., 2021). This data was then used to generate the Alluvial Diagram, where nodes represent the relative contribution of each category, and connecting strips illustrate their relationships, with strip width indicating the strength of association. This approach not only provides a clear visualization of the data but also highlights key trends and linkages in the current research landscape. Additionally, a time-series bar chart comparing Chinese and English literature across categories was produced and included in the appendix to illustrate temporal shifts and linguistic differences in research focus ES classification, ES model and ES-LULC mode of analysis.

2.3 Results

2.3.1 Spatial distribution of MES & LULC research in China

The spatial patterns of MES and LULC research in China reflect both overlaps and distinctions between English- and Chinese-language literature (Figure 2.3-1). Research in both languages is heavily concentrated in the western and southwestern mountainous regions, particularly Sichuan, Yunnan, Guizhou, Xinjiang, and Gansu. However, notable differences emerge in research emphasis and institutional orientation. English-language studies are more frequently conducted in ecologically sensitive regions of global concern—such as arid zones (e.g., Xinjiang, Gansu), transboundary areas (e.g., Yunnan), and high-altitude fragile systems (e.g., the Tibetan Plateau, Sichuan)—often reflecting international research agendas and collaborative projects (Zhu et al., 2024). In contrast, Chinese-language studies are predominantly led by local universities and institutes, focusing on policy-prioritized regions associated with national ecological restoration and poverty alleviation programs, such as Guizhou and western Sichuan (Gao et al., 2014; Yu et al., 2021). This divergence is further evidenced by differing spatial blind spots: English-language research remains limited in Jiangxi, Hunan, and Inner Mongolia, whereas Chinese-language research is scarce in northeastern provinces (e.g., Heilongjiang, Jilin), coastal regions (e.g., Jiangsu, Zhejiang), and the central Tibetan Plateau. While Beijing hosts leading national research institutions, strong regional research capacities are also evident in provinces like Sichuan and Yunnan, particularly in Chinese-language studies.

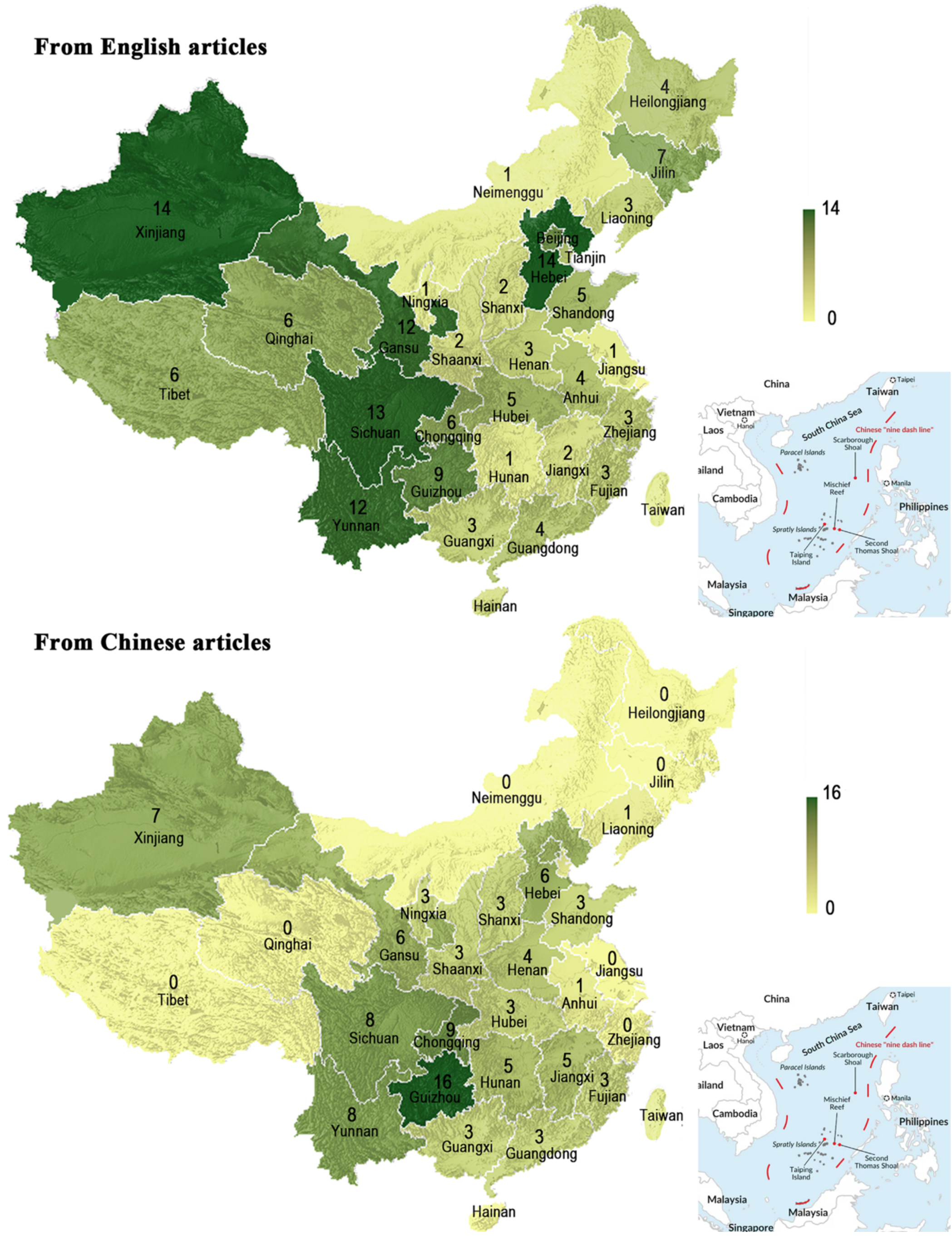


Figure 2.3-1 Geographic distribution of published research Chinese MESs & LULC in English and Chinese research criteria.

2.3.2 Temporal and spatial scales and their determinants

Figures 2.3-2 and 2.3-3 show that research on MES and LULC in China is steadily increasing, with most studies focusing on regional scales (Figure 2.3-2). Spatially, there is a clear rise from 2018 toward present and future-oriented analyses (Figure 2.3-3). In addition, a distinct pattern links spatial scale with study duration (Figure

2.3-4): Larger spatial scales tend to match longer time scales. English-language studies often focus on spatial heterogeneity by short timeframes (<5 years) (Jiangbo Gao et al., 2021; Wu and Dai, 2024), or use longer timeframes (20-40 years) at broad regional scales (10^4–10^6 km^2), supported by long-term remote sensing datasets usually (Liu et al., 2024). In contrast, Chinese studies are concentrated at local scale and intermediate durations (10–20 years), corresponding with national policy cycles such as the Grain-to-Green program (Gao et al., 2014). Despite some variation, both English- and Chinese-language studies predominantly adopt 5–10 year intervals (Figure 2.3-4a, 2.3-4c). A few English studies use finer sampling (1–3 years) for dynamic assessments, while Chinese studies tend to align more consistently with five-year policy cycles.

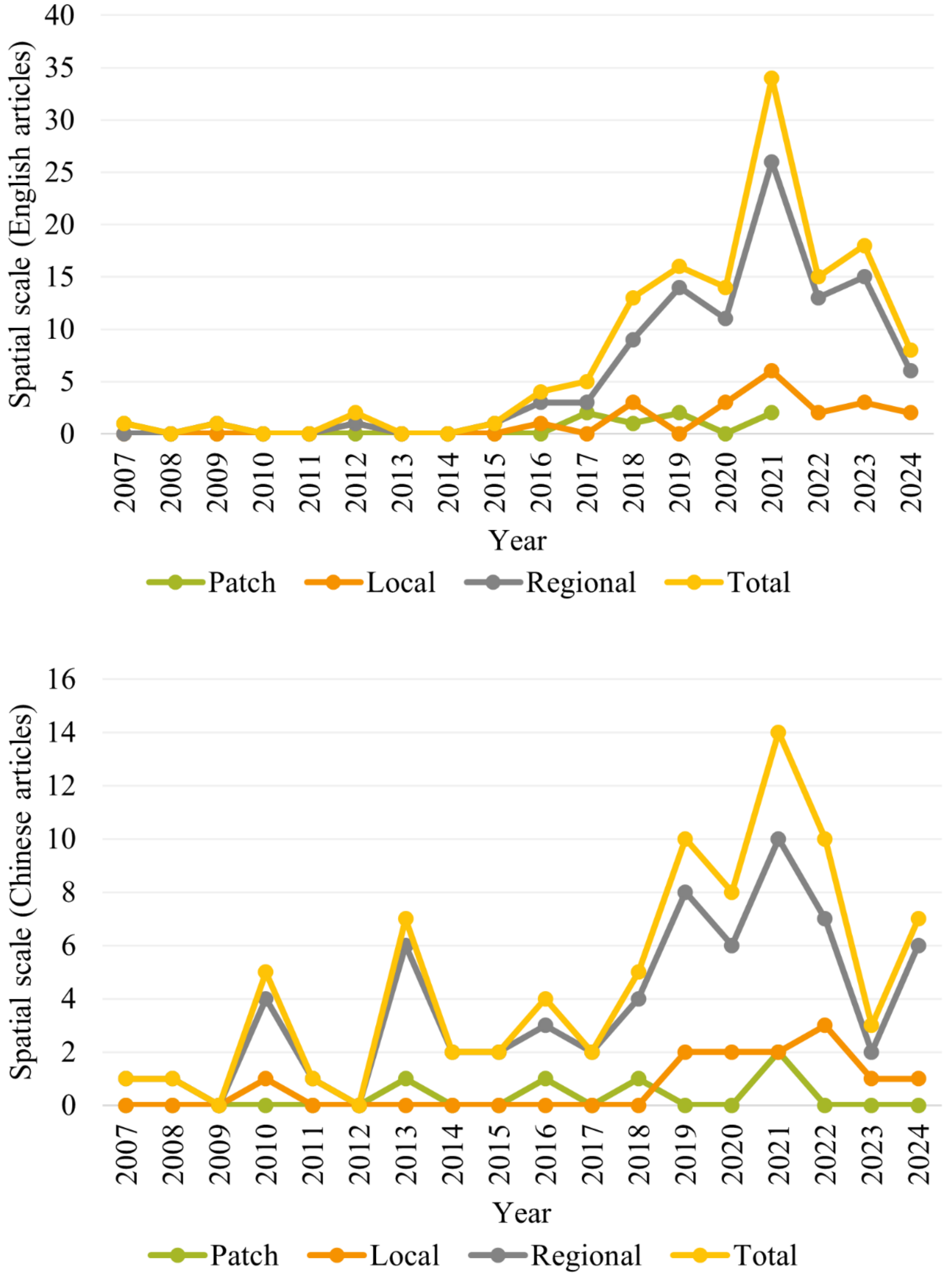


Figure 2.3-2 Spatial coverage of the Chinese Mountainous LUCC & ES studies published between 2007 to 2024 in English and Chinese-language articles.

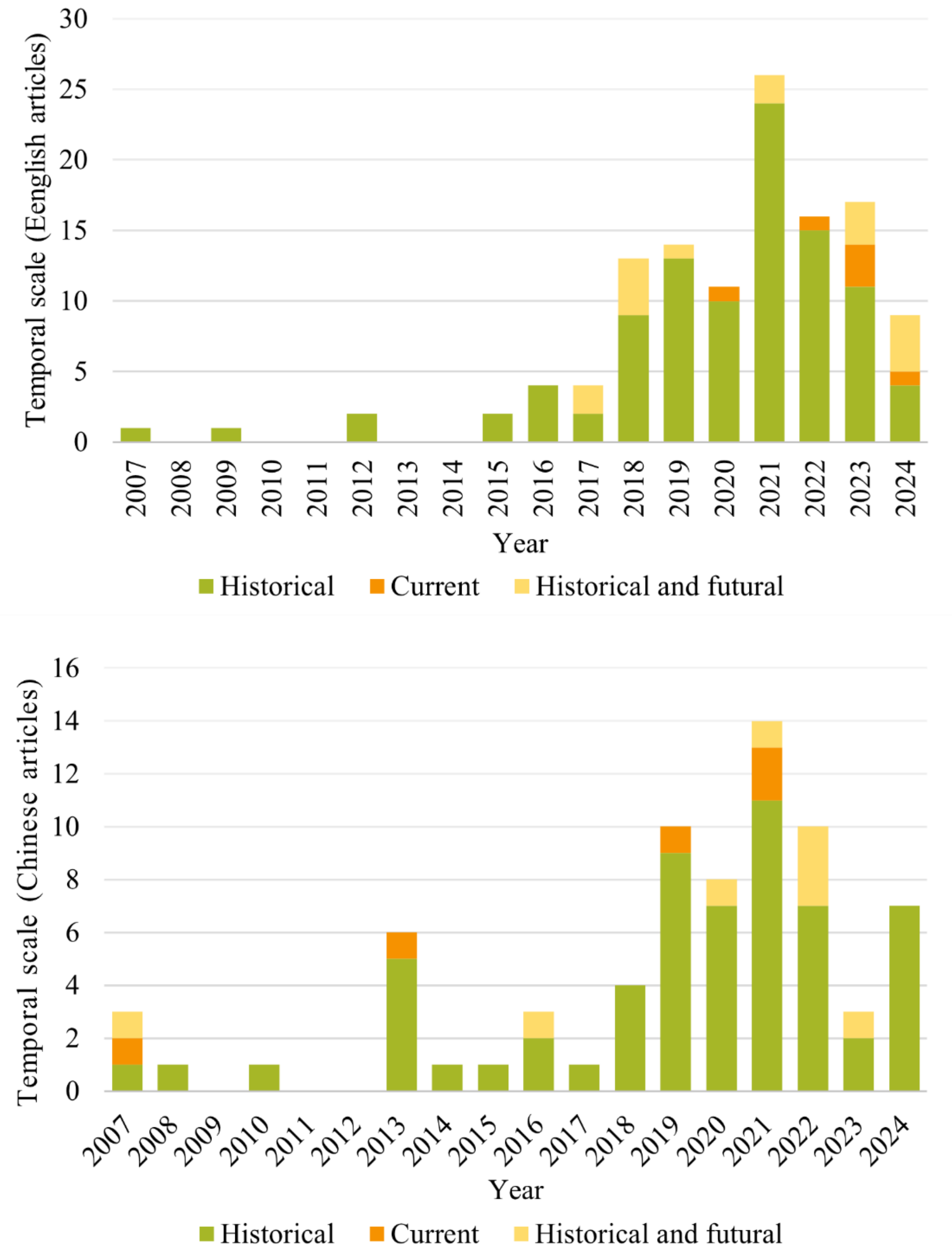


Figure 2.3-3 Temporal orientation of Chinese MESs & LUCC published research in English and Chinese search criteria.

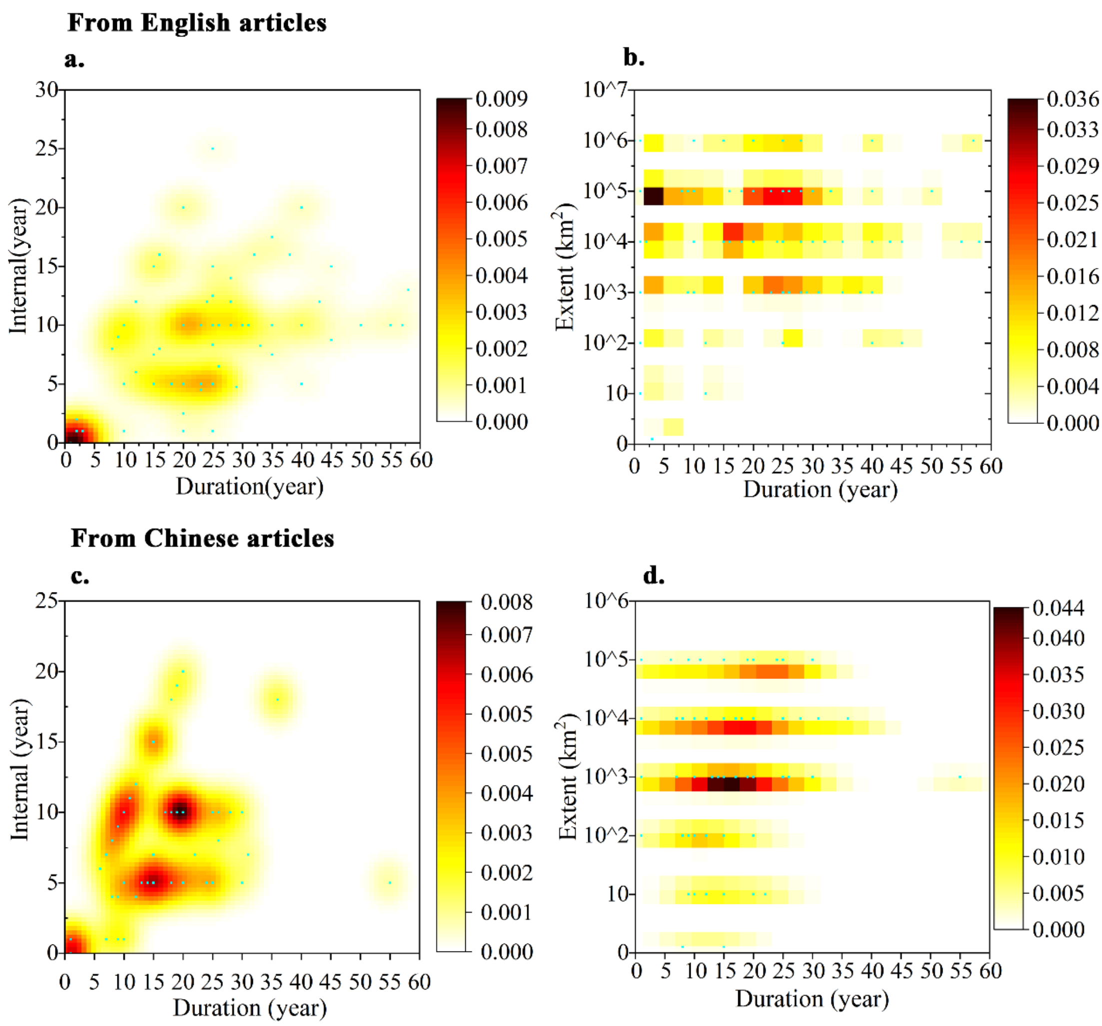


Figure 2.3-4 Kernel density estimates of observational densities within the domains defined by duration and interval (of temporally replicated observations) (a, c); and duration and extent (b, d).

2.3.3 Current trends in Chinese MES & LULC research

This systematic review examined trends in Chinese MES & LULC. Since the release of the Millennium Ecosystem Assessment (MEA, 2005), scholars gradually began to apply its framework to Chinese MES & LULC studies from 2007 onward (Li et al., 2007). Later, the TEEB (2010) and CICES (2011) frameworks, by emphasizing the ES economic valuation and providing a standardized classification system separately, also encouraged a growing focus on ES monetary valuation, statistical analysis for evolution, interrelationships after 2010, and combined spatial overlay after 2012 (Peng et al., 2016; Fu et al., 2015;Wang et al., 2012) (Figure 2.3-7, Figure 2.3-8).

After 2018, driven by the global adoption of the IPBES frameworks (2019), 2030 Sustainable Development Agenda (Colglazier, 2015), and increasing concern over climate change (Masson-Delmotte et al., 2021), the number of publications rose sharply, particularly in English-language articles (Figure 2.3-10). ES Assessment methods shifted from monetary valuation to biophysical and InVEST model increasingly adopted after 2018 in English-language studies, while Chinese-language studies predominantly relied on monetary valuation before 2022 (Figure 2.3-7). Meanwhile, the research focus evolved from ES quantification and correlation analyses toward current ecological security pattern (ESP) and future scenario-based simulations aligned with ecological planning and policy objectives, as well as integrated approaches such as bundle/trade-off analysis (Figure 2.3-8). Some studies aimed to incorporate Chinese MESs & LULC mapping into planning, and link circuit theory to develop ecological security models that safeguard critical ecosystem functions and landscape connectivity against urban expansion and habitat fragmentation (Huang et al., 2020; Yan et al., 2024). Other studies use historical data to simulate future ecological conservation and economic development scenarios, combining visual analyses of Chinese MES & LULC maps to assess and reduce ecological risks (Gao et al., 2021; Guo et al., 2023). These approaches offer practical insights for landscape planning, ecological policy, and management.

In addition, social benefits are a relatively new focus in Chinese MES & LULC assessments. Our review found that although some studies estimated social benefits, these still focused primarily on economic valuation (e.g., tourism value, recreation) (Qian et al., 2019) or payment for ESs (Zhang et al., 2021; Zhang et al., 2018). Especially in English literature, cultural services remain the weakest part of all service evaluations (Figure 2.3-6). However, the assessment that incorporated social benefits found that land use patterns had the strongest impact on tourists' perceptions of various cultural services compared to other services (Lyu et al., 2021), which implies that social benefits have great research potential in the future.

The results of the different spatial scales of the comparative studies reveal the various approaches followed by the studies. In terms of research on Chinese LULC and MES, the regional scale has consistently been the dominant spatial scale in bilingual studies (Figure 2.3-2), it primarily addresses the impacts of LULC on key ESs distribution and changes, explores trade-off relationships, evolutionary trends, and develops the land or ecological decision support ecological security or scenario projections of LULC and ES changes. At the local scale, studies primarily focus on analyzing spatiotemporal dynamics, assessing the effects of LULC on ESs (Yang et al., 2022), and conducting ES valuation (Xiao et al., 2020), with some also constructing local LULC multi-objective Scenarios (Luo et al., 2024; Zhu et al., 2024). Patch scale research is very rare, commonly involves identifying cultural and other service values by stakeholder survey or other first-hand data analysis in villages or parks (Zhang et al., 2020), and simulate the futural land use scenarios (Thellmann et al., 2018).

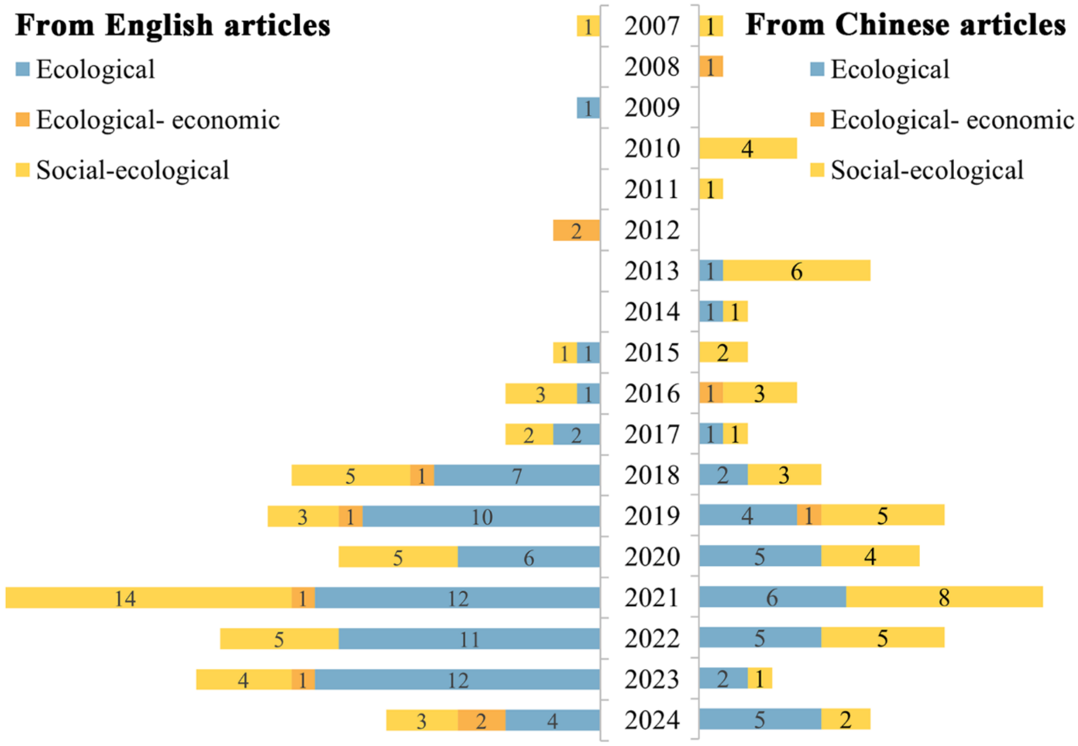


Figure 2.3-5 Temporal distribution of research focus in English- and Chinese-language ES–LULC studies in mountain regions of China.

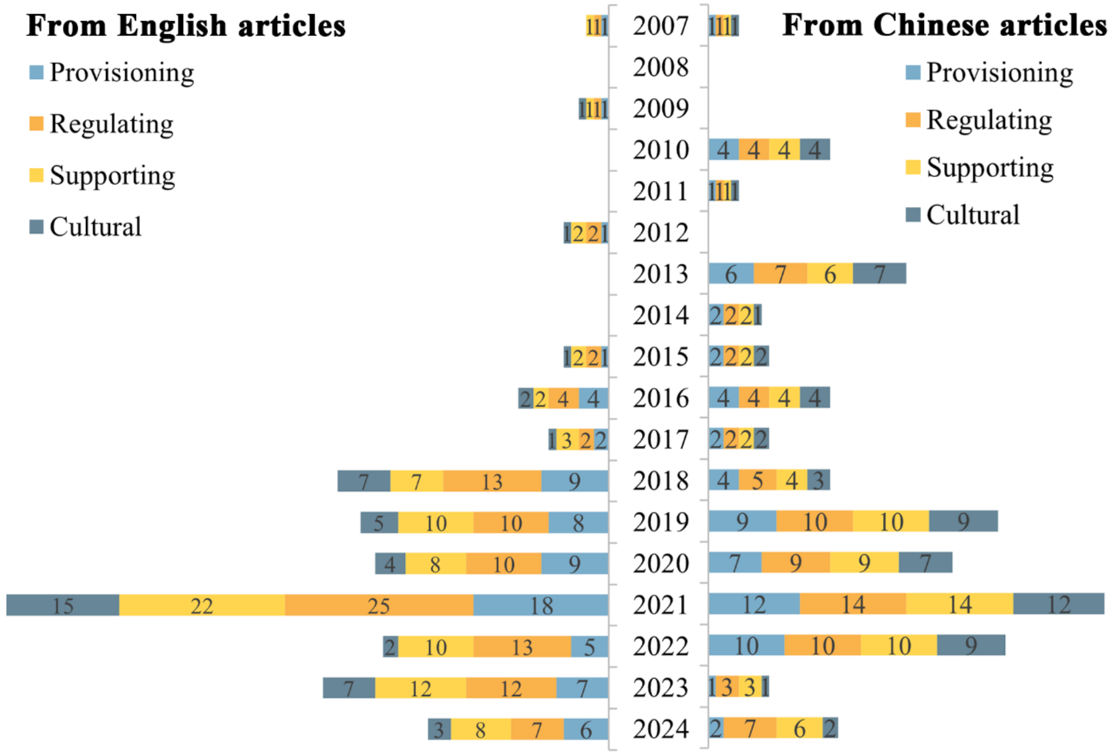


Figure 2.3-6 Temporal distribution of ES types in English- and Chinese-language ES–LULC studies in mountain regions of China.

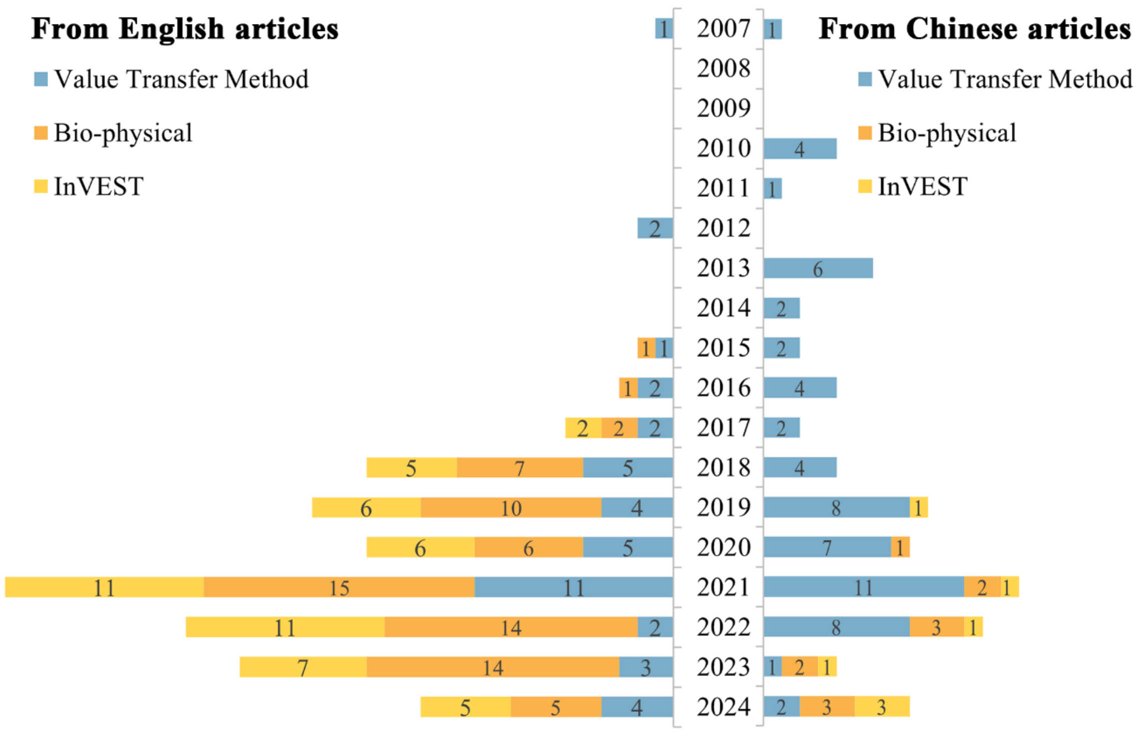


Figure 2.3-7 Temporal distribution of ES models in English- and Chinese-language ES–LULC studies in mountain regions of China.

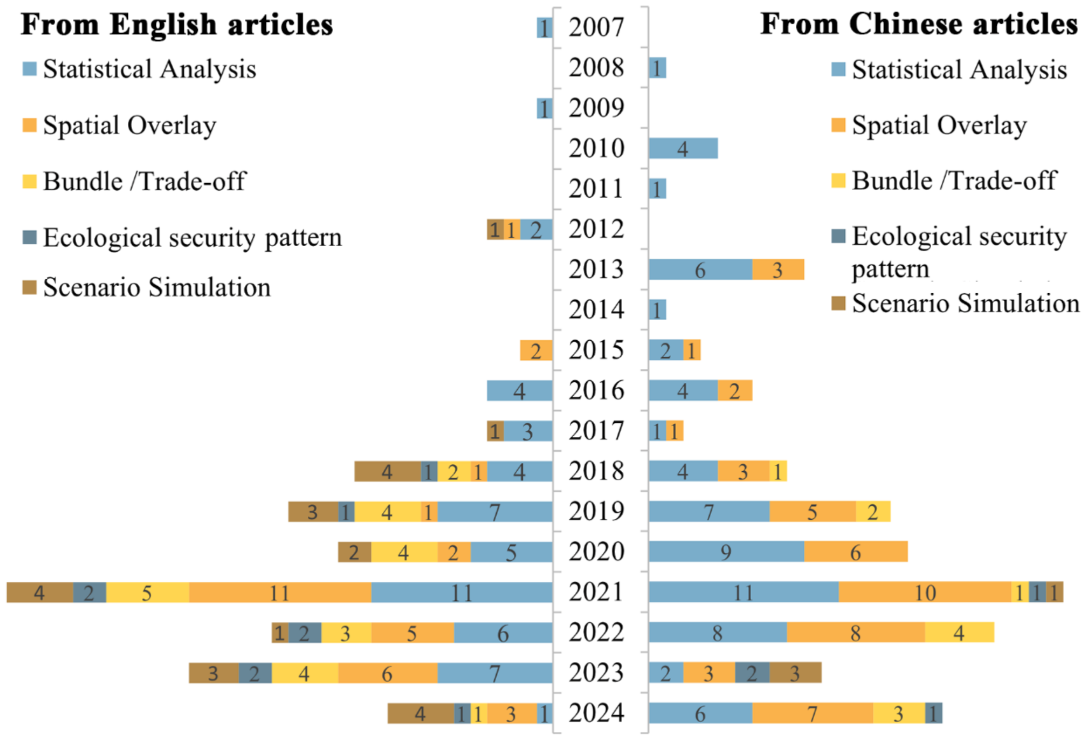


Figure 2.3-8 Temporal distribution of mode of ES–LULC analysis in English- and Chinese-language ES–LULC studies in mountain regions of China.

2.3.4 The concept of ESs in Chinese mountain research

It was found that both regulating services and supporting services were the most represented services in the 121 published studies in English and 82 studies in Chinese (Figure 2.3-9). Regulating services were also the most diverse type of service considered, with soil conservation (84-English, 65-Chinese) being the most involved, gas regulation (43, 72) and climate regulation (40, 61), water quality regulation (29, 59) as well as water flow regulation (32, 51) being relatively popular. Support services were the most commonly mentioned type, due to the fact that mountain research has the highest demand for biodiversity (55,67) assessments. Of the provisioning services, food production (58, 56) was the most assessed component, followed by raw material (41, 51). Although recreation accounts for the majority (29, 39) of cultural service assessments, cultural services overall remain the least addressed category in Chinese MES-LULC research.

Comparisons revealed a strong homogeneity of the Chinese ES categories, which is due to an over-reliance on the revised Chinese Scale of Values of Ecosystem Services as a framework (value transfer method), which includes the 11 most important ES indicators in China, leading to a high intensity and convergence of studies valuing the indicators using the framework, which explains the high mentions of the leisure indicator. Cultural services are the most vacant in mountain studies, since cultural services are more difficult to quantify than other well-established ES models, and valuation methods are not mature, especially regionally and at larger scales.

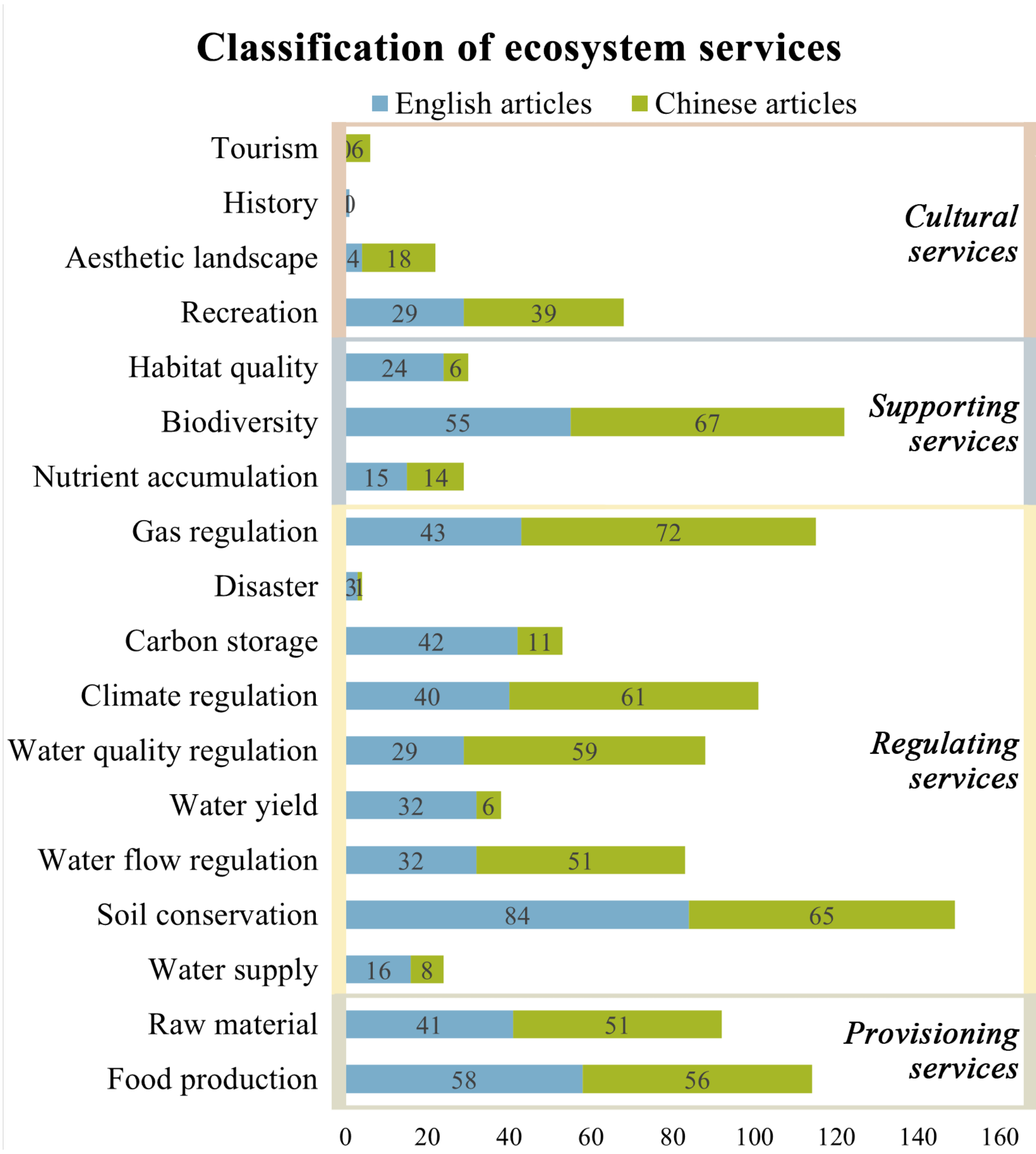
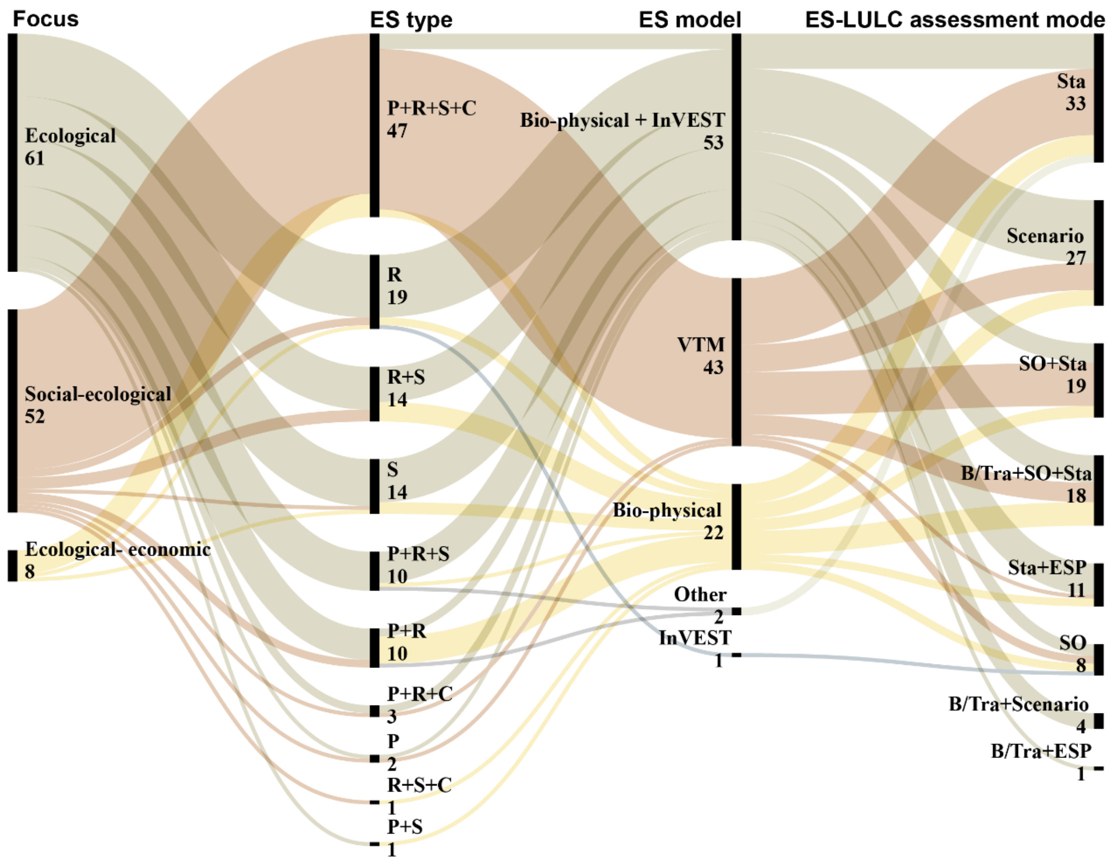


Figure 2.3-9 Number of ES sub-types from all publications of Chinese MESs & LULC research.

2.3.5 Research focus, ES, model and relationship analyses of Chinese MES & LULC

From a methodological perspective (Figure 2.3-10), studies on mountainous regions in China have predominantly adopted the ES valuation - value transfer method (VTM), accounting for 35% of English-language and 75% of Chinese-language publications. These studies typically encompass all ES categories, emphasize the socio-ecological dimension (English-52/121, Chinese-63/82), and ultimately analyse ES and LULC by statistical analysis, spatial overlay, bundle/trade-off analysis, scenario simulation (for Chinese). Beyond this dominant method, ecological focused research (accounting for 50% of the English-language and 21% of Chinese-language studies) employ the InVEST model and/ or biophysical models (e.g., CASA, SWAT, RUSLE), particularly those related to regulating and supporting services and ultimately focus on mapping, temporal statistical analysis, scenario simulations and ESP.



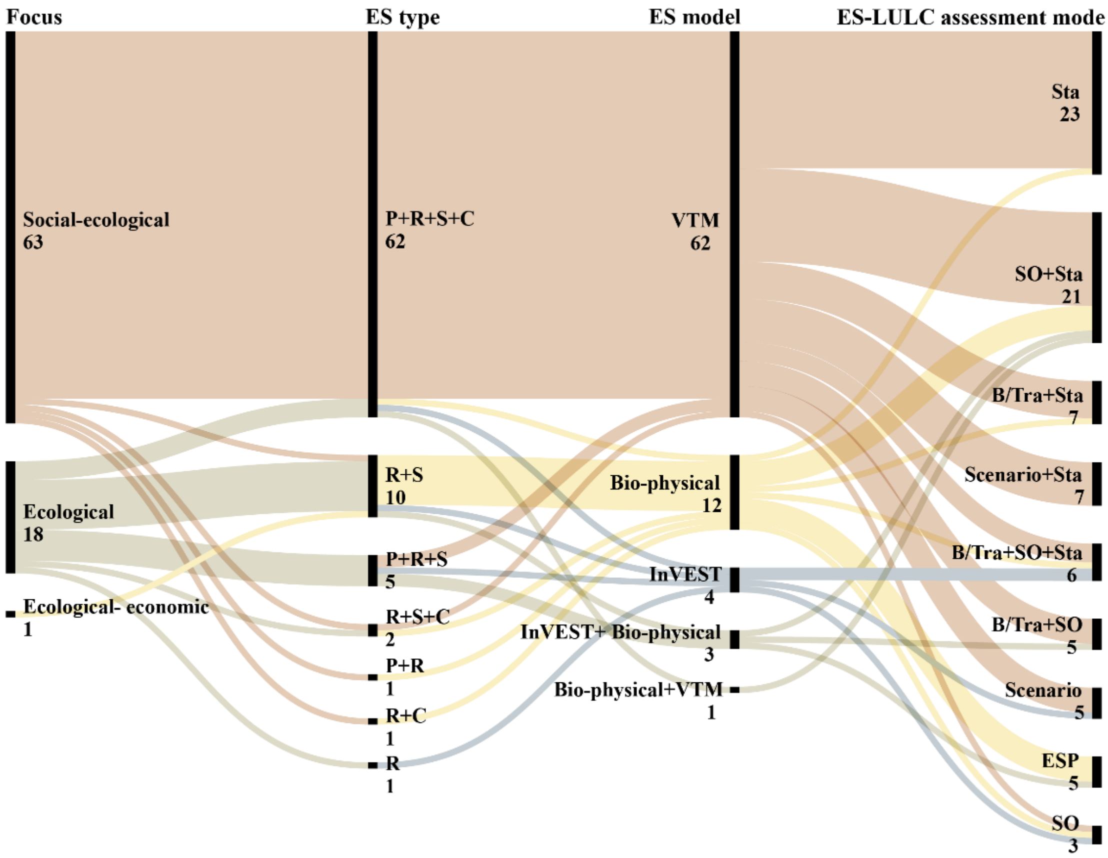


Figure 2.3-10 The Alluvial Diagram for the research focus, ES types, models, and mode of assessment in English (top) and Chinese-language articles (bottom). In ES types, P-

provisioning services; R- regulating services; S- supplying services; C- cultural services. In ES model section, VTM: Value Transfer Method. For mode of assessment part, Sta: Statistical analysis, Scenario: Simulation simulatio, SO-spatial overlay, B/Tra: Bundle/Trade-off, ESP: Ecological Security Pattern. The width of the links corresponds to the mention frequency, and the numbers and labels correspond to the number and type of articles.

2.3.6 ES-LULCrelationship analyses in Chinese mountain studies

There are three known ways in which LULC can change ESs in Chinese mountains: LULC change ESs; changing LU spatial patterns to change ESs; and changing LU intensity to change ESs (Liu et al., 2022). According to these ways of LU influence ES, our finding of reveals that:

1) In previous research, LULC transition matrices and dynamics are the most commonly used methods to study the impact of LULC change on ecosystem services. Based on historical land use data, the study established an ecological value matrix related to land use change to understand the impact of land use change and spatial and temporal changes in habitat quality (Dai et al., 2019). However, although this method is extremely popular, it is concentrated on studies with 10-year intervals within 40 years, and the selected articles lack dense time series of satellite data monitoring LULC studies, which will greatly increase the error caused by sharp fluctuations in land use.

2) A small number of selected studies mentioned LU spatial pattern changes ESs, and most of them used this to study landscape pattern evolution and ESV interaction. Some studies have used landscape indexes to explore the relationship between land use and ecosystem services. For example, the landscape index method has been used to explore the changing characteristics (Su et al., 2012) and interaction of landscape patterns and ecosystems in the past three decades (Yi et al., 2018, Gong et al., 2019), ecological security patterns has been used to develop and optimise for ecological restoration (Li et al., 2022; Wang et al., 2022).

3) At present, only a small part of the selected studies (e.g. Su et al., 2012; Xu et al., 2016) uses the land use intensity method, which can reflect the impact of human

activities, but the response mechanism of ES to land use intensity is not clear, which is not conducive to predicting the impact of land use change on ES in different scenarios. Studying the impact of land use intensity on ES in rural China shows that there is a trade-off between supply services (crop production) and regulation services (soil conservation and climate regulation) with large increases in land use intensity (Xu et al., 2016).

4) In terms of analyzing the relationship between LULC and ESs, InVEST model (Gong et al., 2019; Shi et al., 2021) and ES value transfer method (Ling et al., 2019; Chen et al. 2020) are commonly used to evaluate ecosystem services. Most studies used remote sensing data and GIS-based models (such as hotspot analysis, InVEST model) to examine the ES spatial patterns and the impacts of LULC on ESs (Zhang et al., 2021; Sun et al., 2023). To analyse LULC, the most commonly used method is correlation analysis (Cheng et al., 2019; Sun et al., 2020), scenario simulation method – mostly by Markov model (Zhu et al., 2024), PLUS model (Guo et al., 2023; Wang et al., 2024) FLUS model (Luo et al., 2024) and CLUE model (Gao et al., 2021).

2.4 Discussion

2.4.1 Knowledge gaps and methodological challenges in Chinese MES & LULC studies

This review identifies several key research gaps in the current literature on Chinese MES & LULC. Although similar methodological limitations have been acknowledged internationally, their manifestations in China's mountainous regions remain distinct and unresolved.

First, although 70% (144/203) of the reviewed studies examine the relationship between Chinese MES & LULC, 20% explicitly explore trade-offs or interactions among services (41/203). Most focus on how LULC affects different services individually (Dai et al., 2020; Tian et al., 2022; Wu & Dai, 2024), while giving limited attention to inter-service dynamics or potential conflicts (Goldstein et al., 2012; Gong et al., 2019; Wang et al., 2024). Advanced methods such as service bundles (Lyu et al., 2021), social–ecological networks (Felipe-Lucia et al., 2022), and scenario trade-off modelling (Zhao et al., 2023) are commonly applied in China and international ES research but have yet to be widely adopted in China's mountainous regions.

Second, temporal discontinuity and lack of long-term monitoring remain major obstacles. Although international research has increasingly emphasized the importance of time-series analyses to identify regime shifts and ecological thresholds (Sardanyés et al., 2024; Bathiany et al., 2024), only a minority of Chinese mountain studies include more than three temporal observations (J. Sun et al., 2023) or apply time-series methods (Thellmann et al., 2018; Gao et al., 2022). This hinders the detection of critical change points and tipping points, thereby limiting the ability to define safe operating spaces and delaying proactive management responses(Zhang et al., 2015; Hossain et al., 2017).

Third, cultural ESs (CES) are particularly difficult to assess due to their overlapping categories (e.g., recreation, spirituality, aesthetics) and their non-material, context-dependent nature, which makes them challenging to quantify and integrate into standard assessment frameworks (Yang and Cao, 2022). These challenges are compounded by the subjectivity of cultural values, the lack of standardized indicators, and the difficulty of translating localized meanings into broader policy contexts. To address these limitations, international research has explored emerging methods such as participatory mapping (García-Díez et al., 2020; Gottwald et al., 2022), narrative approaches (Kim and Son, 2021), and artificial intelligence and social media-based analysis (Mouttaki et al., 2022). However, these methods still face practical limitations in integrating CES into LULC planning and governance, and most applications have been concentrated in urban contexts (Huang et al., 2024; Wen et al., 2024). Their use in mountainous regions of China remains limited, further constraining the institutionalization and cross-scale integration of CES in spatial decision-making (Kosanic and Petzold, 2020).

In addition, one of the other major methodological challenges is the difficulty in developing a multi-scale approach to the entire MES. Our review shows the overreliance on secondary data (192 out of 203 total) makes a homogeneity of available indicators and methods. China's research on MES excessively relies on the

VTM, which is based on national-scale assessment tables of ES values (Xie et al., 2008). It is suitable for large-to-medium scale, coarse-grained or comprehensive ecological accounting, does not account for the ecological contributions of subdivided areas (e.g., saline land and construction land) and fails to consider spatial heterogeneity (Huang et al., 2007; Guo et al., 2019). Small-to-medium scale ES assessments are primarily conducted through ES modelling. However, different models have various limitations, complexity constraints and data gaps (e.g., the revised universal soil loss equation (RUSLE) is inadequate for deep gullies in mountainous areas (Bogdan et al., 2016); the InVEST model-water yield model overlooks the interaction between surface runoff and groundwater and neglects topographic effects (Fu et al., 2017; Wang & Dai, 2020)). Coupled with a lack of consensus among researchers on selecting indicators and appropriate methods, which hinders the integration of results across wider spatial and temporal scales (Boerema et al., 2017). The absence of a comprehensive, multiscale integrated assessment approach impedes policymakers from effectively managing MES and strategically planning LULC (Ren et al., 2023).

Finally, obtaining high-quality, long-term representative data on certain Chinese MESs & LULC indicators poses a significant challenge. The diversified LULC resolution and ES indicators lead to limited comparability in different geographical studies, thereby limiting efforts to conduct consistent cross-scale analyses and long-term assessments (Duan et al., 2021).

In summary, although international studies have already highlighted these general challenges, the Chinese mountain context exhibits persistent and context-specific gaps. Addressing these requires methodological adaptation, locally relevant data generation, and enhanced integration of biophysical and socio-cultural perspectives.

2.4.1.1 Opportunities and Future Directions

Research patterns in China’s mountainous regions are shaped by several contextual factors. National ecological policies—such as Grain-for-Green and Ecological Redlines—strongly influence the spatial focus and valuation priorities of Chinese MES & LULC studies. Limited long-term ecological monitoring also restricts access to time-series data, hampering model calibration and system-level analysis. In addition, the region's complex topography and socio-ecological heterogeneity challenge the direct application of global models developed for more uniform or lowland areas. These factors have contributed to the emergence of a localized, policy-driven research logic in China.

To address these issues, future assessments should prioritize flexible, cross-scale frameworks tailored to mountainous conditions (Chen and Chi, 2022; Le Provost et al., 2023). Although modular biophysical models (InVEST, ARIES, RUSEL, SWAT) and evaluation tools (ES Value Transfer Matrix, ESTIMAP) exist, their application remains fragmented and poorly aligned with land use planning needs (Spake et al., 2017; Wang et al., 2020; Li et al., 2024). Data scarcity—particularly for high-resolution LULC, socio-economic, and ecological indicators—further constrains robust assessments (IPBES, 2019; Lyu et al., 2021). Therefore, future efforts should focus on building flexible, scale-sensitive assessment architectures that can synthesize model outputs, accommodate data gaps, and support translation of ecological metrics across spatial planning units (Schirpke et al., 2020; Sun et al., 2022). Practical strategies may include combining remote sensing proxies (Deeksha et al., 2023), expert knowledge(Haida et al., 2016), benefit transfer approaches (Badamfirooz et al., 2021), and process-based models in hybrid workflows (Li et al., 2024). In addition, methods to standardize inputs (Paul et al., 2021), quantify uncertainty (Stritih et al., 2019), and validate models using local knowledge (Evangelista et al., 2024) are essential. Establishing operational pathways for upscaling fine-scale indicators (such as through area-weighted indicators and nested spatial frameworks) can help embed ES metrics into planning systems and support more responsive governance in data-poor mountain landscapes (Wolff, 2023).

Moreover, CES – particularly those related to spiritual values, sense of place, and cultural identity – remain underrepresented in current assessments due to their intangible and context-dependent nature (Kosanic and Petzold, 2020). In mountainous regions, where cultural landscapes and traditional practices are often deeply embedded in land use patterns, understanding how LULC change influences CES is especially critical (Li et al., 2025). Future frameworks should integrate participatory mapping (Xu et al., 2020), narrative valuation (Kim and Son, 2021), and digital trace analysis (e.g., social media, mobile data) (Wang et al., 2023) to better capture the spatial distribution and perception of CES. Incorporating CES into modular, multi-scale assessments will help reflect the full value of landscape transformation and support more inclusive land governance(Yang and Cao, 2022).

Human activities (LULC change) directly alter nature, and these changes in turn affect the generation and provision of ES, creating the largest number of knowledge gaps due to the complex feedback mechanisms involved (Mastrángelo et al., 2019). Over longer time scales, feedbacks between society and ecosystems are considered particularly relevant for designing and implementing effective and sustainable production and LULC, and for keeping impacts of direct anthropogenic pressures on natural systems well within safe ecological limits (Mastrángelo et al., 2019; Jiangbo Gao et al., 2021; Nayak et al., 2024). Therefore, future research questions can be: What the feedback and trade-off relationship exist between Chinese MES & LULC under long time series? How can system dynamics or integrative simulation approaches be adapted to better represent the dynamic coupling between Chinese MES & LULC? How can the concept of safe ecological limits be defined and operationalized through social–ecological system (SES) models in Chinese mountainous landscapes? What are the key spatial configurations and thresholds of ecological security patterns in China's mountainous regions (Jia et al., 2023)? In the future, China's mountain land use planning and management will implement the most effective policies through dynamic simulation to achieve a sustainable win-win situation for society and the ecosystem.

Future projections of ESs interactions under land use development scenarios and management actions need to be considered (Su et al., 2012), to develop more reliable trade-off evaluation systems to assess ecosystem responses to extreme conditions and different policies (Yu and Han, 2016; Shi et al., 2021). What’s more, Explore multiple nature reserve management options to determine the proportion of ecological sources and develop suitable methods to determine the spatial extent of ecological corridors, ecological nodes and ecological barriers to extraction (Lin et al., 2021). Finally, to establish a multi-level ecological compensation model, the willingness to pay of protection stakeholders and the willingness to accept of farmers should be incorporated based on the quantified biophysical and economic value of ESs, so that compensation standards reflect both ecological value and stakeholder acceptance (Fan et al., 2019; Gao et al., 2020; Liu et al., 2023).

2.5 Conclusion

This study provides the first systematic review of the relationship between Chinese MES & LULC. The bilingual literature synthesis reveals several key findings. Research in this field began in 2007 and has grown rapidly since 2018, reflecting increasing attention to the dynamics of mountain SES.

(1) Current studies lack an integrated, adaptive, and cross-scale assessment framework tailored to the environmental and socio-ecological characteristics of mountainous regions in China.

(2) Chinese literature predominantly emphasizes statistical analysis of socio-economic valuation and spatial overlay, whereas English studies focus more on ecological processes and dynamic modelling approaches, including InVEST, biophysical models, scenario simulations.

(3) English-language studies generally adopt longer time series and finer temporal intervals, supporting better understanding of system evolution and trade-offs.

(4) Notable differences are also found in spatial scale and temporal focus. English-language studies often cover broader regions, whereas Chinese studies have more local. While most research remains retrospective, the number of future scenario-based analyses, though still limited, is growing rapidly.

These findings suggest the need for integrated, multi-scale methodologies and long-term datasets to capture the co-evolution of Chinese ES and LULC in mountain SES. By identifying research gaps and highlighting divergent approaches between Chinese and international studies, our review contributes to informing more resilient Chinese mountainous land management and ES governance.

Chapter 3 Uncovering the co-evolution of land use change and ecosystem services in Shandong province, China

Many studies have explored the relationships between ecosystem services (ES) and land use/ land cover (LULC) changes, but understanding the synergistic evolution of their complex socio-ecological dynamics is still limited in China. This study provides a comprehensive time-series analysis of ES and LULC spanning 1950 to 2022 in Shandong province of China, offering valuable insights into the sustainability of these systems. We derived evolutionary trends by analysing satellite map data, official government data, and literature data; developing a conceptual model of causal feedback of LULC and ES by the Granger causality test; and analysing the relationships of ES with LULC and GDP using the Environmental Kuznets Curve (EKC) model and sequential principal component analysis. The trend analysis reveals that urban sprawl is increasingly encroaching on most of the natural land, especially agricultural land, posing a serious threat to food security. The EKC modelling demonstrates that economic growth continues to fuel urban expansion without reaching a sustainable tipping point. Our conceptual model suggests that urbanization increases the demand for provisioning services, deteriorating key regulating services, in a synergistic relationship with tourism. Ultimately, these factors collectively undermine regional ecosystem resilience. Our results suggest that the socio-ecological systems in Shandong experienced weakening connectivity and heightened vulnerability between 1980 and 2022, indicating a shift toward functional disturbance and possible reorganization, with the possibility of approaching tipping thresholds. Our findings provide valuable insights for policymakers in China and other global mountains for land management and ecosystem restoration to avoid the collapse of SES.

3.1 Introduction

Increasing human-induced land use/ land cover (LULC) changes are contributing to ecosystem services (ES) degradation: globally, the continuous exploitation of natural resources and land has increased provisioning services, but accelerated the degradation of regulatory and support services (Lawler et al., 2014), with approximately $40 trillion in global ecosystem service losses, and irreversible land degradation directly affecting half of humanity (Vander Esch et al., 2022). In China, exponential economic development has led to faster LULC changes. Urbanization, abandonment and return of farmland to forest, and land intensification have led to a significant decline in the total value of ecosystem services (Cao et al., 2021; Li et al., 2020), and a large part of the loss comes from mountain areas, which is not only caused by the vulnerability and sensitivity of mountain areas to LULC, but also since the high diversity of mountain ecosystems makes the most abundant and intensive contribution to ES (Rogora et al., 2018; Schirpke, Tscholl, et al., 2020). To understand the complex relationships between LULC and ES in mountainous areas, the concept of co-evolution is required to be introduced: it is based on a longer time series and captures the slow social and ecological processes from a dynamic perspective, for understanding how the interacting factors evolve and co-evolve over time (Thompson & Pagel, 2001; Zhang et al., 2015). We are attempting to apply this concept to the LULC-ES relationships, to gain insights into the complexity and trade-offs of the socio-ecological systems for inclusion in the land use management plan (Dearing et al., 2014b)

Research on the interactions of mountainous LULC-ES has expanded in recent years. Scenario-based projections are increasingly used to explore future dynamics (Jiang et al., 2023a; Zhao et al., 2023b), but many studies rely on short-term or coarse-resolution data, limiting insights into long-term system feedback and transitions (Pătru-Stupariu et al., 2020; Hasan et al., 2020). While some pioneering work has explored non-linearities in SES (Lin et al., 2019, 2024), the co-evolutionary dynamics between ES and LULC remain underexamined – especially from a long-term systems perspective in China’s coastal mountainous regions. In the Chinese context, several studies have addressed ES–socioeconomic linkages (Lin et al., 2019, 2024; Zhang et al., 2015), but LULC change has not been sufficiently integrated as a coupled biophysical and social driver. Other studies focused on time-series datasets on soil and land use (e.g., Wang et al., 2023; He et al., 2017) have rarely addressed the multi-scalar feedback between ecological processes and socioeconomic change.

Understanding these dynamics is essential for detecting tipping points (i.e., the critical threshold beyond which the system shifts into a qualitatively different and potentially irreversible regime), for assessing resilience (i.e., the system's capacity to maintain key ES and LULC functions despite disturbances), and for evaluating connectivity (i.e., strength and persistence of dynamic interactions over time), finally, informing land governance in ecologically sensitive areas. This study presents the first long-term co-evolutionary analysis of ES and LULC in China's coastal mountainous regions by integrating time-series data to uncover dynamic patterns and feedback, thereby addressing a critical gap in the context of rapid urbanization. We strive to achieve the aim of the study by focusing on the following three specific objectives:

1) To quantify long-term trends in ES and LULC by collecting and analysing time-series data on ES and LULC indicators as well as related economic indicators to quantify the long-term trajectories.

2) To explore the relationships between ES and LULC changes driven by social and economic development, using the environmental Kuznets curve (EKC) and sequential principal component analysis (PCA) to explore and investigate relationships and connectivity within SES as a measure of resilience.

3) To develop a conceptual system model of each indicator, exploring the relationships and feedback within ES indicators and between ES-LULC indicators to understand the processes and drivers of co-evolution. In addition to the synthesis of the previous analysis, this study used the Granger causality method to help conceptualize a dynamic feedback framework to understand the interplay mechanism between ES and LULC.

The results of this study may contribute to defining safe and just operating spaces (i.e., environmental and social thresholds that maintain ecological integrity while ensuring basic human well-being) that can assist policymakers in developing regional sustainable management strategies and managing land use for achieving net zero (i.e., a balance between carbon emissions and sequestration) in mountainous regions and coastal areas of China (O'Hogain et al., 2018).

3.2 Data and methods

3.2.1 Study area

In our systematic review of LULC and ES in mountainous areas (Chapter 2), a lack of research has been identified for the east coast of China, especially in Shandong Province (only 3 articles focused on specific habitats or urbanization). Furthermore, there was no research on the analysis of co-evolution to explore the relationships between ES and LULC. As the province with the second-largest population, third-largest economy, and first-largest vegetable (88 million tons in 2021) and aquatic products in China (*China Statistical Yearbook*, 1999-2023), Shandong's ecosystem health and stability will support the food security and well-being of most Chinese provinces and more than 20 neighbouring countries. Therefore, this research chooses Shandong Province as a case study to explore the socio-ecological evolution of mountainous areas on the east coast of China.

Shandong Province is located on the eastern coast of China with a total land of about 157,900 square kilometres and a population of more than 100 million, making it the country's second most populous province (*China Statistical Yearbook*, 2023). Shandong is the more mountainous province, and it is also the province with the third longest coastline in China (around 3345 km) (Li et al., 2023). The province has a warm temperate monsoon climate, with simultaneous rain and heat, an average temperature of 11-14 ℃, and an annual average precipitation of 600-750 mm, but more than half of the precipitation is concentrated in the summer, with drought disasters occurring in the spring and autumn (*Shandong Statistical Yearbook*, 1983-2022). As a populous and economic province in eastern China, the urbanisation rate has increased from 13% in 1985 to 64% in 2022 (Ren et al., 2023) (Figure 3.2-1). Urban expansion has exacerbated land degradation and fragmentation, and the implementation of some policies such as land reform and the policy of returning farmland to forests has also driven extremely rapid changes in land use in mountainous areas. These changes in land use types have led to unprecedented changes in the ecosystem structure, putting great pressure on sustainable development (Fan & Xiao, 2020). Exploring the relationship between ES and its synergistic evolution with LULC in Shandong Province as an example is beneficial for other similar mountainous and coastal regions in China and beyond.

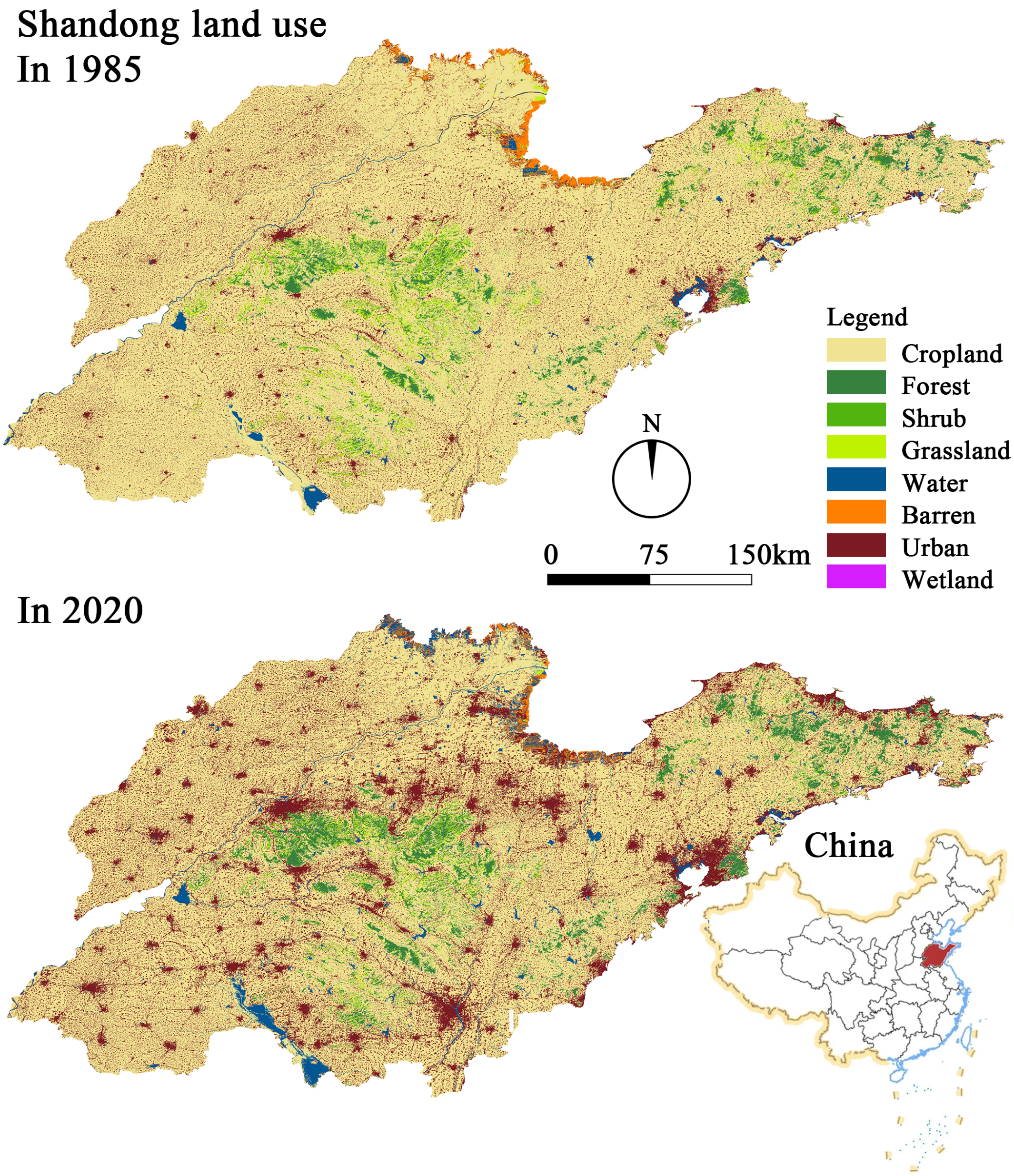


Figure 3.2-1 Shandong Province is located on the eastern coast of China. There have been significant changes in land use over the past 35 years.

3.2.2 Data sources: ES, LULC, and social indicators

3.2.2.1 Ecosystem services

The selection of ecosystem service (ES) indicators for Shandong Province was guided by three criteria: the availability of long-term data (1978–2022), the degree to which each indicator reflects key regional environmental challenges, and their measurability using consistent statistical sources. In total, eleven indicators were incorporated, covering provisioning, regulating, supporting and cultural services.

Provisioning services comprised four indicators from 1978 to 2022, represented by food production, aquatic production, timber production, and water supply. Food production was measured as the combined annual output of grains, vegetables, fruits and oilseeds, while aquatic and timber production captured the total provincial yield of fisheries and harvested wood resources in 1978 to 2022. Water supply reflected the total volume of surface water, groundwater and other sources available for use. All provisioning service data were obtained from the Shandong Statistical Yearbook (1978–2022), and annual values were derived directly from the statistical records.

Regulating services were characterised using indicators of climate variables (temperature and precipitation), air emissions, wastewater discharge, soil erosion and natural hazard regulation. Meteorological data (1950–2022) were obtained from the National Meteorological Data Centre, while all other regulating-service indicators—including air emissions represented by carbon dioxide emissions (1982–2022), wastewater discharge (1982–2022), soil erosion (1985–2022) and natural hazard–related data—were sourced from the Shandong Statistical Yearbook. Natural hazard regulation was represented by the annual area of crops affected by droughts, floods, low-temperature damage, gale events and other extreme hazards, which reflects the province's long-term capacity to buffer climatic and environmental shocks. Overall, these regulating-service indicators collectively depict the long-term trajectories of atmospheric pressure, hydrological stress, land degradation and disaster-buffering capacity.

Habitat quality, representing supporting services, was assessed using the dataset produced by Zheng and Li (2022) based on the InVEST Habitat Quality model for the period 1980–2020. Their study used land-use types as model inputs and incorporated anthropogenic disturbance factors (e.g., built-up land, roads), together with their impact distances and sensitivity parameters, to estimate habitat degradation under various threat pressures. An annual habitat quality index was then generated to reflect long-term trends in regional habitat condition and landscape integrity. This study directly uses the published habitat quality results as secondary data for analysis.

Cultural services were represented by annual tourist numbers (1978–2022) obtained from the Shandong Statistical Yearbook, used as a measurable proxy for cultural and recreational service use. Other cultural services were excluded due to the lack of consistent, long-term and regionally comparable data.

3.2.2.2 Land use/land cover change

The time series of the 1985-2021 land use raster dataset (30m*30m) in Shandong Province for this study was obtained from the Landsat-based China Annual Land Cover Product (CLCD) produced by Wuhan University (https://zenodo.org/records/8176941). Using 335,709 Landsat images on Google Earth Engine, and stable training samples extracted from CLCD, several temporal metrics were constructed from all available Landsat data and fed into a random forest classifier to obtain classification results. The final land types were categorised into nine primary land types, namely agricultural land, forest, shrub, grassland, water, wasteland, impermeable land, wetland, and snowfield. Among these land types, only eight land types were extracted and analysed, as there were no permanent snowfields for land use. We calculated the raster image data as area data of different land types through QGIS as a data source for land use time series analysis.

3.2.2.3 Economic and Demographic Change

Changes in ES and LULC are driven by economic and demographic indicators, and it is necessary to include changes in economic and demographic indicators in the assessment of drivers. We use GDP (total GDP, primary, secondary, and tertiary GDP, and GDP per capita) as a proxy for the economic indicators, and the demographic indicators include urban and rural populations. Both the economic and demographic data were collected from the *Shandong Statistical Yearbook* (1983-2022).

3.2.3 Methods

3.2.3.1 Multivariate time series analysis

Our goal is to analyse multiple time series of ES and LULC data and investigate the co-evolutionary relationships between LULC, socio-economic variables and ES.

We need to investigate the correlation and dynamic structure of this dataset and to understand and conceptualize these relationships between LULC and ES. Therefore, this research uses Granger causality tests to explain the observed interactions between ES and LULC at different time lags (in years) (Barbosa et al., 2016; Shojaie & Fox, 2022). Given lag lg, this study estimate the binary unrestricted vector autoregressive equation for the two variables (X t and Y t) as follows:

$$X_t = \beta_0 + \sum_{i=1}^{lg} \beta_i X_{t-i} + \sum_{i=1}^{lg} \alpha_i Y_{t-i} + \varepsilon_{1t} \qquad (3.1)$$

$$Y_t = \alpha_0 + \sum_{i=1}^{lg} \gamma_i Y_{t-i} + \sum_{i=1}^{lg} \delta_i Y_{t-i} + \varepsilon_{2t} \qquad (3.2)$$

Where β, α, γ and δ are the coefficients and ε t is the residual term. The null hypothesis of Granger causality ("Y does not Granger cause X" and/or "X does not Granger cause Y") can be specified as follows:

$$H_0: \alpha_1 = \alpha_2 = \cdots = \alpha_m = 0,\ H_0: \delta_1 = \delta_2 = \cdots = \delta_m = 0 \qquad (3.3)$$

The hypotheses tested can be realised by a F-test, which can be implemented using a model consisting of two regression steps:

$$X_{t_u} = \beta_0 + \sum_{i=1}^{lg} \delta_i X_{t-i} + \sum_{i=1}^{lg} \alpha_i Y_{t-i} + \emptyset_{1t} \quad \text{.......................................} \quad (3.4)$$

$$X_{t_r} = \beta_0 + \sum_{i=1}^{lg} \beta_i X_{t-i} + \mu_{1t} \text{...} \quad (3.5)$$

The following equation was then used to calculate the residual sum of squares:

$$RS\ S_u = \sum_{T=1}^{T} \theta_{1t}^2 \text{...}(3.6)$$

$$RS\ S_r = \sum_{T=1}^{T} \mu_{1t}^2 \quad \text{..}(3.7)$$

Finally, to compare the residual sum of squares with the F distribution and the (p, T - 2p - 1) degrees of freedom, this study use the following equation:

$$F(p, T - 2p - 1) \sim \frac{\frac{RS\ S_r - RS\ S_u}{p}}{RS\frac{S_u}{T-2p-1}} \text{...}(3.8)$$

We inevitably rejected the null hypothesis if the value of the F-statistic was found to exceed the critical value of the chosen level of significance (the significance level was set at $p \leqslant 0.05$).

Finally, this study plotted the filtered results as causal loop diagrams to visualise the results of Granger causality.

We used the Granger causality test through Eviews software (Alhakimi, 2018; Xu et al., 2013) to investigate the co-evolutionary relationship between ES and LULC over time and plotted the causal loop of the system through Kumu (https://kumu.io/) based on the results of Granger causality test (Figure 3.3-5 and Figure 3.3-6). We analyzed the Granger causality through Eviews software by setting the delay years as 1-10 years and manually tested all the causality within ten years using an Excel spreadsheet to reject the null hypothesis (significance level of $p \leqslant 0.05$), and finally, the delay year with the highest significance level of the causality result was taken as the delay year data. If both directions of the null hypothesis are significant, it's a bidirectional relationship; if only one side of the null hypothesis is significant, it's a unidirectional relationship. In the causality feedback diagram, this study manually screened and extracted direct relationships for summarization due to the presence of non-direct causal relationships in the Granger causality section. Our causal feedback plots reveal causal flow relationships between LULCs, between LULCs and ESs, and between ESs.

3.2.3.2 Environmental Kuznets Curve Analysis

The Environmental Kuznets Curve (EKC) theory (Dinda, 2004) is a hypothesized relationship between various indicators of environmental degradation and per capita income. This theory predicts that the degree of coupling between economic growth and environmental degradation remains strong until a point is reached where wealth leads to investment into cleaner industrial processes. In this study, the EKC curve for the period from 1950 to 2022 was derived from the plots of different ESs and LULCs against GDP per capita.

3.2.3.3 System connectedness

According to network theory, the resilience of a SES is strongly shaped by the degree of interconnection among its key variables (Coban et al., 2022; Scheffer et al., 2015; Zhang et al., 2015). In this study, system connectedness is defined as the statistical strength of associations among SES variables, following the framework of Dearing et al. (2014). Higher connectedness indicates stronger coupling among subsystem components, allowing disturbances to propagate more easily through the system and thereby reducing flexibility and resilience. System stability is defined as the ability of the system to maintain its structure and function under internal or external perturbations. Increasing connectedness therefore implies declining stability and a heightened risk of systemic failure.

Sequential Principal Component Analysis (PCA) is commonly used to assess systemic risk by capturing changes in the covariance structure of variables over time. An increase in the first principal component (PCA1) eigenvalue indicates that a larger share of system variance is dominated by a single mode, reflecting strengthened coupling and rising connectedness, and therefore greater systemic risk and lower stability (Billio et al., 2012). This research applies the approach to the time-series indices representing the Shandong ES and LULC and the socio-economy over the period from 1950 to 2022. This study calculates covariances using a 20-year moving window PCA that includes together provisioning and regulating services from 1950 to 2021, as well as together ES services and LULC and together ES and GDP from 1980 to 2021. Only the results from the 20-year window are used, as different window sizes give similar results. All datasets have PCA 1 + PCA 2 values > 0.5, which is preferred for connectivity analyses.

3.3 Results

3.3.1 Trends of ecosystem services

Figure 3.3-1 displays the trend of ES in Shandong Province, where the record of provisioning services shows dramatic changes from 1950 to 2020. The total agricultural production of Shandong province has increased tenfold between 1949 and 2022, in which crop production has been growing especially after 1978 (reform and opening up). However, the most important growth after 1990 is contributed by vegetable production, which is due to the establishment of a vegetable industrial complex in Shouguang city, Shandong province. This became "the home of vegetables" in China to deliver vegetables to most of the northern provinces of China. After 2000, Shandong's vegetable production was maintained at around 80 million tonnes, which is steadily at the top of the national list; fruit production rose slowly after 1990 when the economy gradually developed.

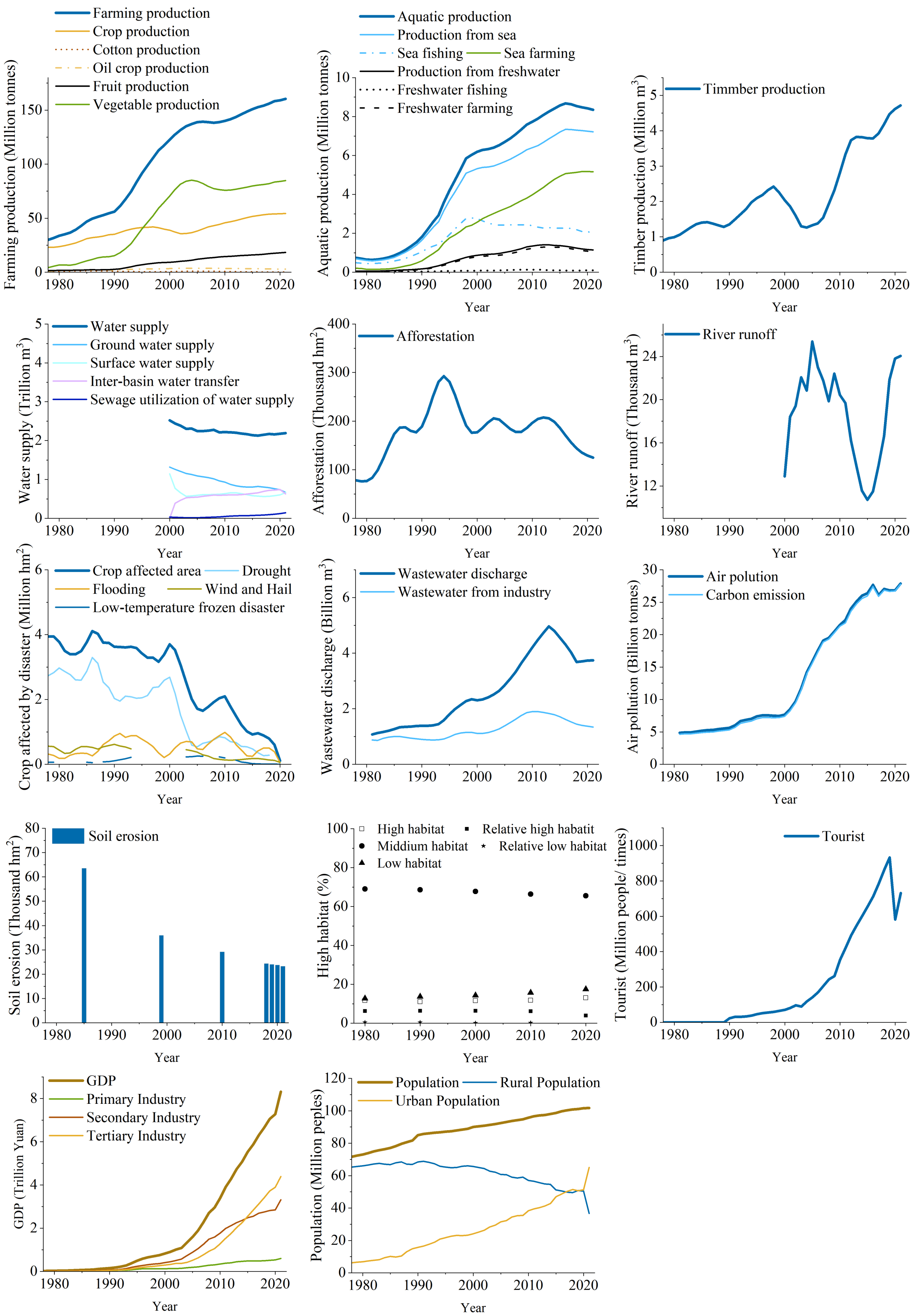


Figure 3.3-1 ES and social-economic trends in Shandong Province from 1950 to 2022 (Shandong Statistical Yearbook, 2022; Zheng & Li, 2022).

Timber supply increases nearly fivefold from 1978 to 2022. Industrial afforestation peaked during 1990 and remained high for the next 20 years before declining. This may be due to the implementation of a large-scale reforestation policy.

Shandong Province is three-sided and surrounded by the sea, and the fishery economy contributes a quarter of Shandong Province's economic growth. Fishery production began to rise exponentially after 1985, and after 1995, as a result of the implementation of the policy of marine fishing moratoriums, marine fishery capture began to grow slower, with mariculture growing rapidly and gradually replacing marine capture.

The shortage of water resources has been a major bottleneck constraining economic and social development in Shandong. Shandong Province is a region of extreme water scarcity, with 4% of the world average (only 298 m^3 of water per capita). But it uses 1% of China's total water to irrigate about 5% of China's agricultural land. Surprisingly, it produces 8 % of the national grain and 11 % of the vegetables, supporting about 7 % of the whole population and supporting about 7 % of the country's total GDP. Over the past 20 years, there has been a gradual decline in water supply, with groundwater supply dropping by half, and the shortfall being made up by the South-to-North Water Diversion Project, which accounts for 20% of Shandong's total water supply year-round, and wastewater reuse technologies are gradually playing a minor role in the water supply.

With economic and technological developments, there have been significant changes in regulating services. Among the disaster indicators, this study assessed the area of crops affected by natural hazards. Between 1955 and 2000, hazards severely affected crop health, with drought being the most significant threat to food security (about 3/4 of the total disaster threat). However, with the development of weather forecasting techniques and agricultural technologies such as drip irrigation and greenhouses, the impact on crops is gradually disappearing. Sewage discharges and gaseous emissions are the main sources of pollution. Sewage emissions peaked in 2013 after the introduction of policies to regulate environmental pollution, and emissions have declined rapidly and are being held at a steady level. Carbon emissions are the mainstay of gaseous emissions, with a gradual sharp increase to 2.7 billion tonnes after 2000. In contrast, soil erosion halved between 1985 and 2021 (Figure 3.3-1). Climate change (Figure 3.3-2) has been significant over the last 70 years, with annual temperatures rising by 1.5 °C between 1950 and 2022, while annual rainfall has declined by about 150mm (from 850mm of 1950-1965 to 700mm of 1965-2022), increasing the threat of drought in the region. The most significant increase in temperature has been in the spring (from 11.5°C in 1955 increasing to 15°C in 2021), with rainfall shrinking more in the spring (from an average of 40 mm in 1950-2010 to 30mm in 2010-2022) and summer (from an average of 180mm of 1950-1965 to 140mm of 1965-2022).

Habitat quality and tourist numbers (Figure 3.3-1) represent support and cultural services, respectively. Between 1980 and 2020, the quality of habitats showed a polarising trend: the area covered by high habitat quality (11.64 %-12.98 %) and low habitat quality (12.63 %-17.44 %) was gradually increasing, while the predominantly intermediate quality of habitats showed a slight decrease (69 %-65 %). The number of tourists increased exponentially from near zero to 0.85 billion with the growth of GDP from 1990.

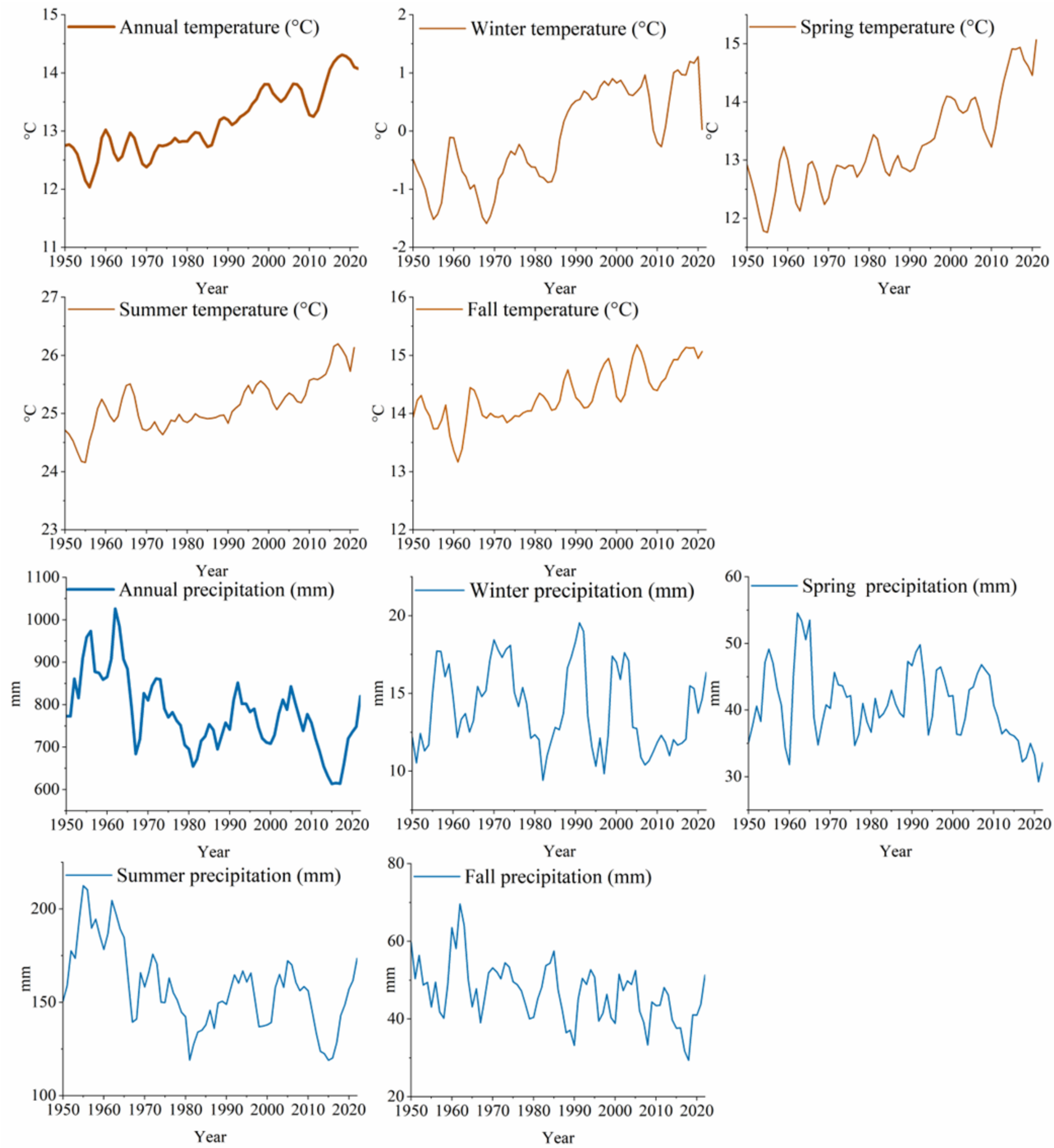


Figure 3.3-2 Trends of annual and seasonal average temperature and rainfall from 1950 to 2022 in Shandong province.

3.3.2 Trends of LULC change

As shown in Figure 3.3-3, in the past 35 years, land use types in Shandong Province have been dominated by arable land, with a serious loss of arable land (11.55 % of the total area), plummeting from about 80 % of arable land in 1985 to 68.45 % in 2021. Shrubs (83 % have disappeared in 35 years), grassland (56 % have lost in 35 years), unused land (86 % have declined in 35 years) and wetland areas (93 % have lost in 35 years) decreased significantly, while the land use types that increase significantly are water covered area (55 % have increased in 35 years), woodland area (24 % have increased in 35 years), and urban and rural residential land use (56 % have increased in 35 years).

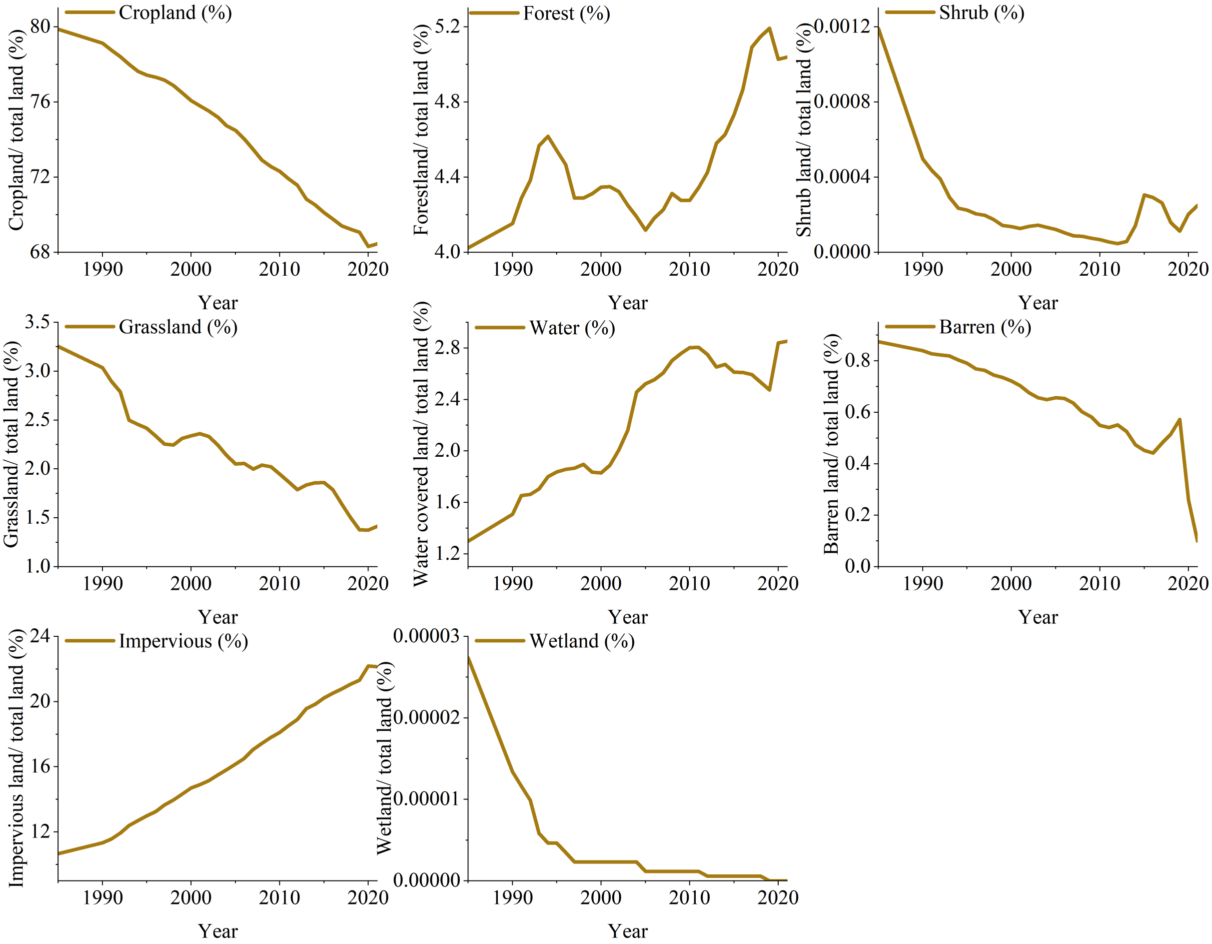


Figure 3.3-3 Land use trends in Shandong province from 1985 to 2022.

From the causal loop of the coevolution in LULC (Figure 3.3-4), urban expansion has led to a decrease in barren land, wetland, shrubland and grassland, but the demand for nature from urbanisation has led to an expansion of woodland and water area: shrubland and barren land have been covered by forestland, and the increase in water area due to the loss of shrubs and barren land has led to a decrease in the area of wetland. The reduction of agricultural land is not only due to the increasing woodland and water-covered land but also encroached by the land for construction. Overall, in the last 35 years, urban sprawl and water and woodlands favoured for urban aesthetics have rapidly replaced the area used for other LULC types.

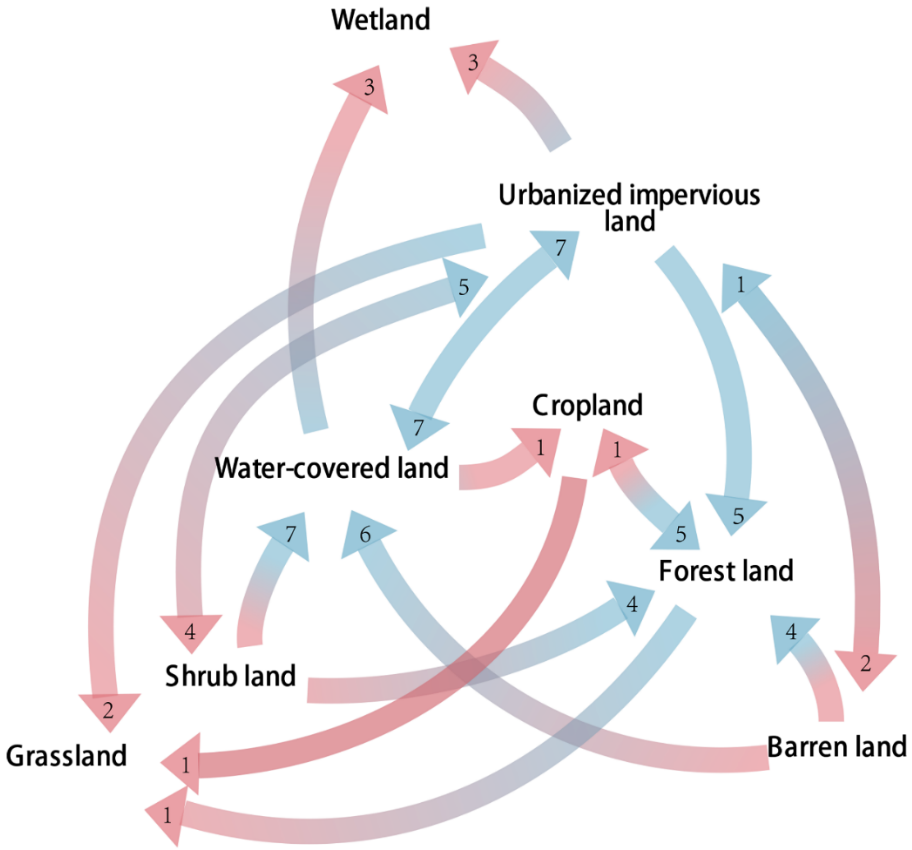


Figure 3.3-4 Causal loop diagram of coevolution of LULCs. Blue indicatesan increase and red indicates a decrease. In the feedback loop, if the arrow colors are all monochromatic, it represents positive feedback, and whereas a change in the arrow color indicates a balancing feedback loop.. Numbers indicate the number of years by which the causal effect is delayed..The relationship is between economic growth and environmental change.

Over the past 40-60 years, environmental degradation has increased rapidly at very low income level and only began to levelled off when GDP per capita reached about 20,000 Yuan per year (Figure 3.3-5) (Zhang et al., 2015). Agricultural and aquatic production increased rapidly as GDP approached 20,000 Yuan, and then levelled off. Timber harvesting shows that demand for timber grows fastest when GDP is between 30,000 to 50,000 Yuan, before levelling off once GDP surpasses 50,000 Yuan. The growth rate of carbon emissions begins to plateau when GDP reaches around 15,000 Yuan. Sewage emissions peak at approximately 55,000 Yuan, after which they decline and stabilise as environmental protection policies and stricter regulations are introduced at higher income levels.The area of low habitat quality continues to grow with the economy and has not yet hit an inflexion point. In contrast, high habitat quality declines rapidly at very low incomes, followed by a gradual exponential rebound with economic development. Soil erosion is also most severe at incomes less than 10,000 Yuan, after which the area of erosion stays steadily low.

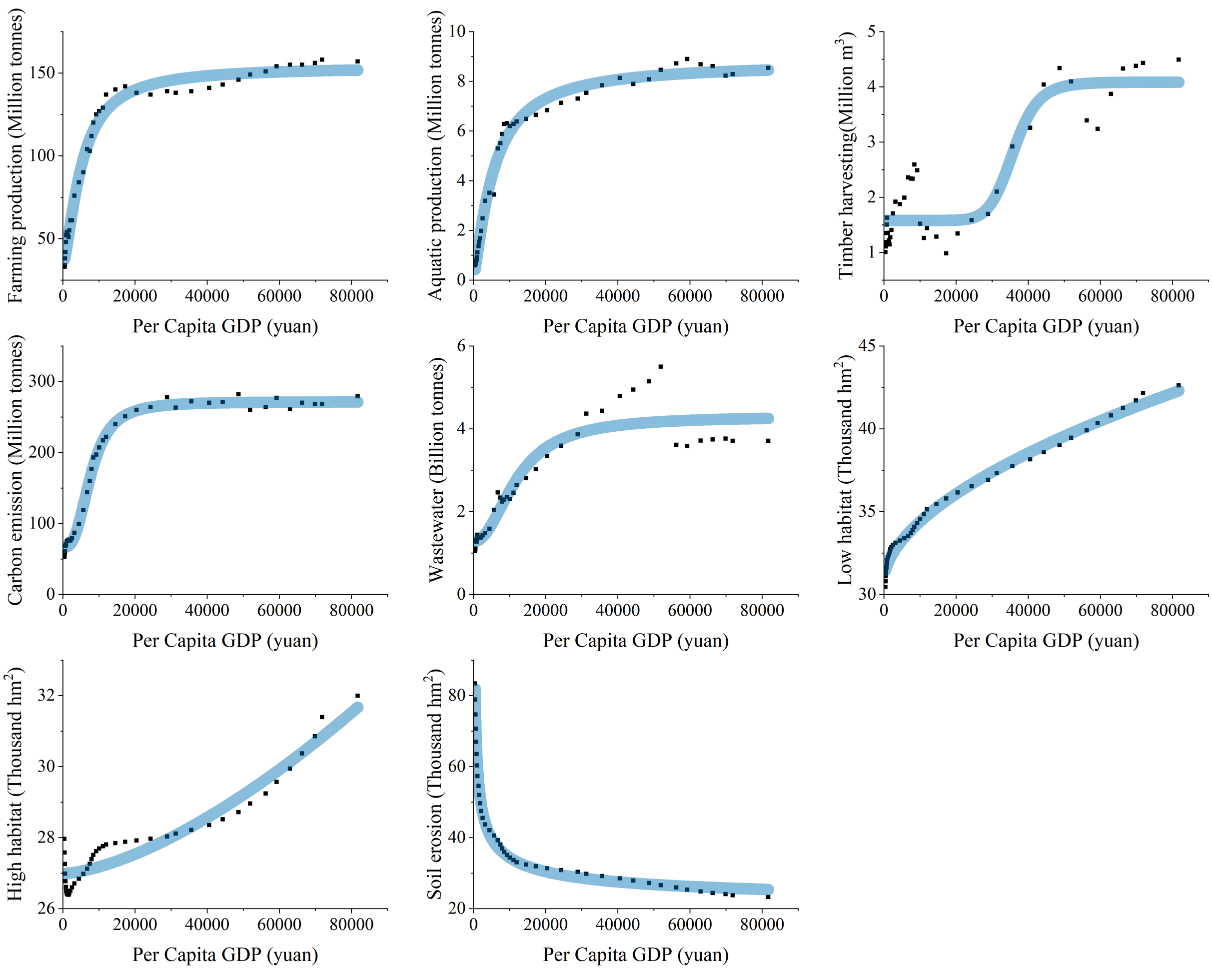


Figure 3.3-5 The relationship between ES and GDP per capita is modelled through EKC. When per capita GDP is below 10,000 Yuan, people solve hunger and livelihood problems (through agriculture, fishing, forestry production) at the expense of the environment (rapidly increasing carbon emissions and sewage discharges, rapid habitat destruction, rapid soil loss). With economic growth, the provisioning services and carbon emissions have gradually tended to a stable high level, and water pollution and soil erosion have been effectively controlled. Habitat restoration requires a better economic foundation in the future to level off.

Poverty is an important driver of land degradation (Figure 3.3-6). Agricultural land, grassland, wetlands and unused land experience rapid degradation when per capita income is below 10,000 Yuan.

Wetland area declines extremely rapidly at low income levels (below approximately 8,000 Yuan per capita) and approaches near-zero levels thereafter, remaining relatively stable at very low values as income continues to rise. Urban land, forest land, and water area gradually increase in size with the promotion of the economy, although forest land expands only after per capita income exceeds 40,000 Yuan and tends to stabilise once income surpasses 70,000 Yuan. Urban land increases rapidly at lower income levels, continues to grow steadily thereafter, and has not yet reached its inflection point. Water area rises sharply until income reaches about 8,000 Yuan per capita, after which it begins to fluctuate around a stable level.

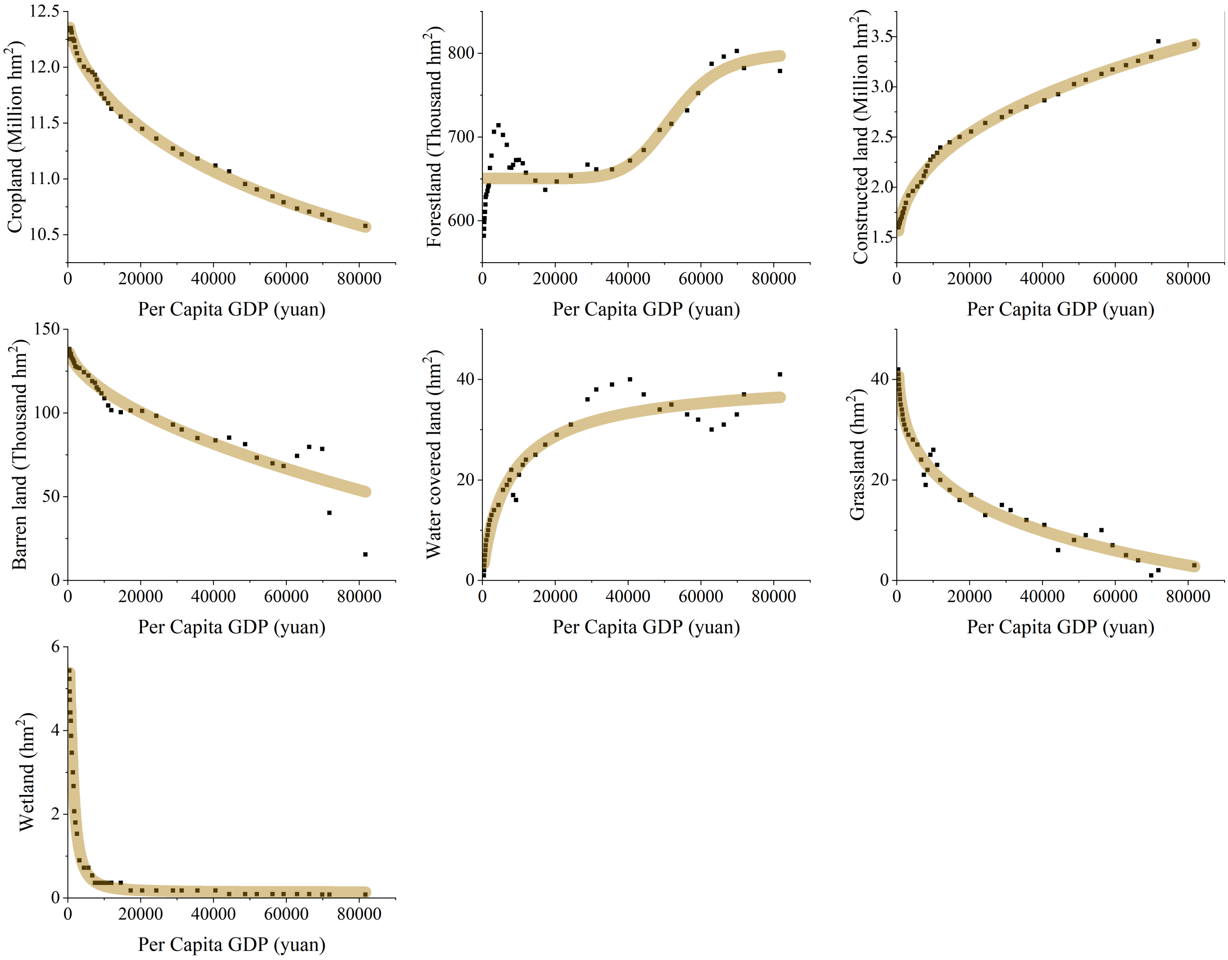


Figure 3.3-6 The relationship between LULC and GDP per capita is modelled through EKC. When per capita GDP is below 10,000 Yuan, people solve hunger and livelihood problems (through agriculture, fishing, forestry production) at the expense of the environment (rapidly increasing carbon emissions and sewage discharges, rapid habitat destruction, rapid soil loss). With economic growth, the provisioning services and carbon emissions have gradually

tended to a stable high level, and water pollution and soil erosion have been effectively controlled. Habitat restoration requires a better economic foundation in the future to level off.

The causal relationship of land use change has been mentioned in Section 3.3.2 (Figure 3.3-4), while there is a co-evolution between land use change and ES (Figure 3.3-7). Land use drives ES change, and is also strongly influenced by ES (Table 3.3-1). In the ES, the increase in aquatic production was due to urbanisation and the expansion of watered areas, yet it had negative feedback with wetland areas. Agricultural land yields rose probably because more water bodies solved the irrigation problem, but more irrigation demand also left fewer wetlands. Agricultural production and urban expansion form a reinforcing feedback loop.

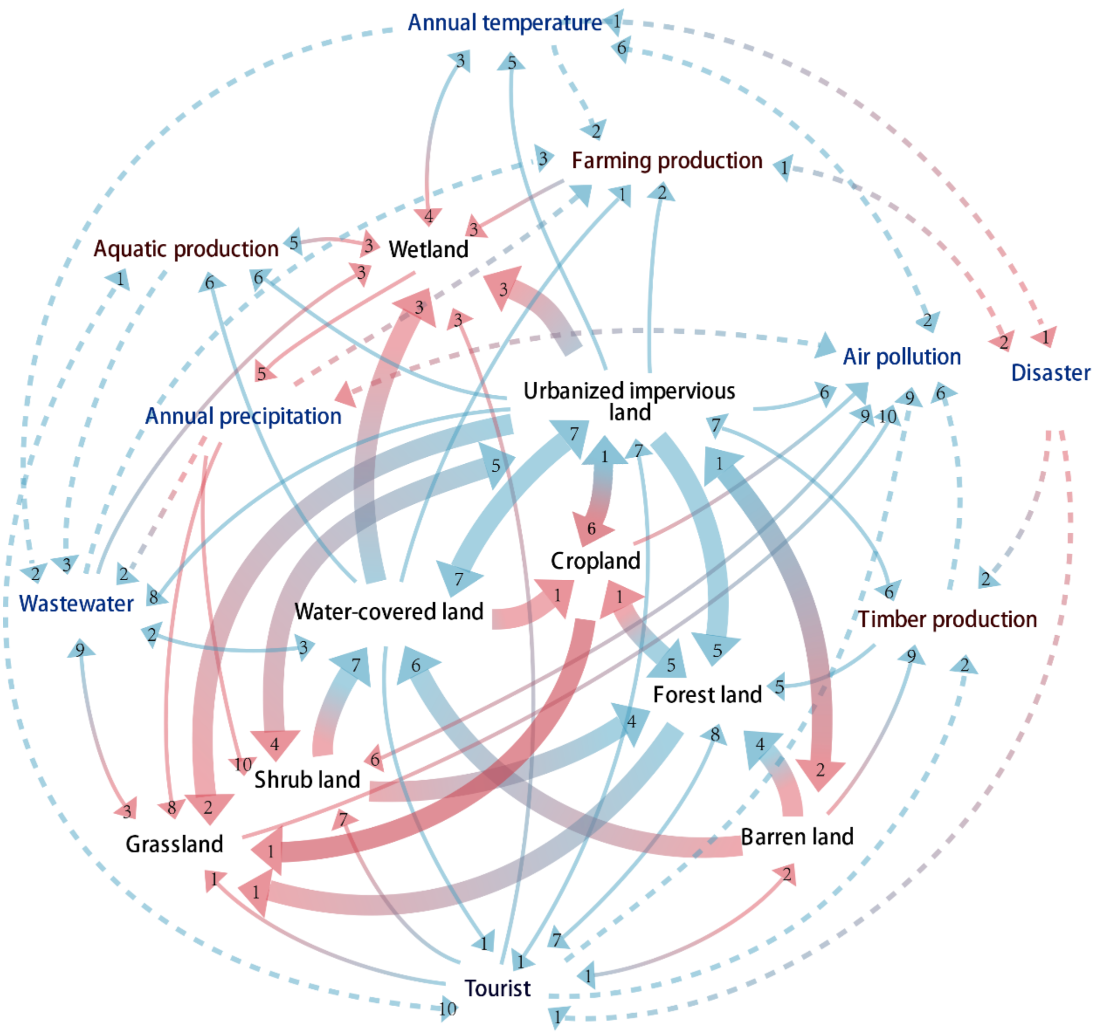


Figure 3.3-7 Causal loop diagram of coevolution of LULC, ES and LULC, and in ESs. The thick solid arrows show the causal relationship between land use changes. The thin solid arrows are the causal relationships between land uses, and the thin dashed arrows are the causal relationships between ES. Blue represents an increase in this variable and red

represents a decrease in the variable. In the feedback loop, if the arrow colors are all monochromatic, it represents positive feedback, and if there is a transition in the arrow color, the feedback is balanced feedback. Numbers imply causal effect delayed response years.

In the regulating service, urban expansion and the reduction of farmland and shrubland increased air pollution, especially carbon emissions; at the same time, the increase in water pollution caused by urban expansion created negative feedback with the reduction of grasslands, and positive feedback with watershed areas, which exacerbated the reduction of wetlands. Under a changing climate, declining annual precipitation and more frequent drought events first reduce wetland extent, and this loss of wetlands, in turn, further weakens local buffering capacity and accelerates the degradation of shrubs and grasslands, eventually leading to a series of balancing feedbacks at a lower level of ecosystem functioning. Urbanisation also increases temperatures and further stresses wetland areas (Table 3.3-1).

Table 3.3-1The ES and LULC relationship matrix. " + " means both indicators increase or decrease at the same time, forming positive feedback. " - " means that one indicator is increasing and the other is decreasing, creating negative feedback. "0" means that there is no significant correlation between the two indicators.

Factor	Urbanization↑	Cropland↓	Shrub↓	Grassland↓	Wetland↓	Water↑	Barren↓	Forest↑
Air pollution↑	+	-	-	-	0	0	0	0
Water pollution↑	+	0	0	-	-	+	0	0
Precipitation↓	0	0	+	+	+	0	0	0
Temperature↑	+	0	0	0	-	0	0	0
Aquatic production↑	+	0	0	0	-	+	0	0
Farming production↑	+	0	0	0	-	+	0	0
Timber production↑	+	0	0	0	0	0	0	+
Tourist↑	+	0	-	-	-	+	-	+

The number of tourists is a proxy for cultural services. Urban expansion and tourist growth are mutually reinforcing, and the boom in tourism has contributed to the expansion of woodlands, with larger water areas attracting more tourists to visit. However, the rapid development of tourism and urbanization leads to the faster disappearance of grasslands, shrubs and wetlands, and there is also a negative feedback relationship with the sharp decline in barren land (Table 3.3-1).

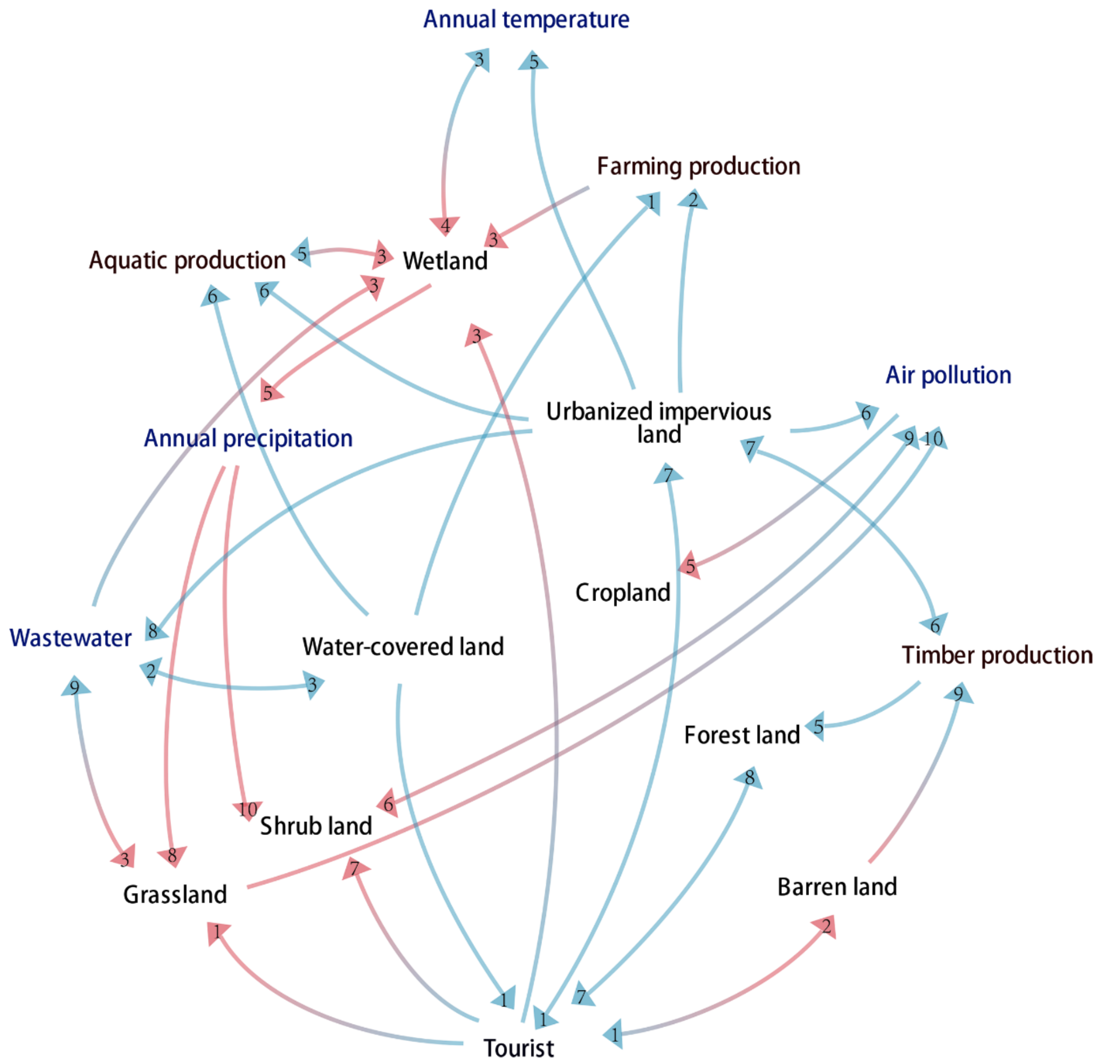


Figure 3.3-8 Causal loop diagram of coevolution of ES and LULC. Blue represents an increase in this variable and red represents a decrease in the variable. In the feedback loop, if the arrow colors are all monochromatic, it represents positive feedback, and if there is a transition in the arrow color, the feedback is balanced feedback. Numbers imply causal effect delayed response years.

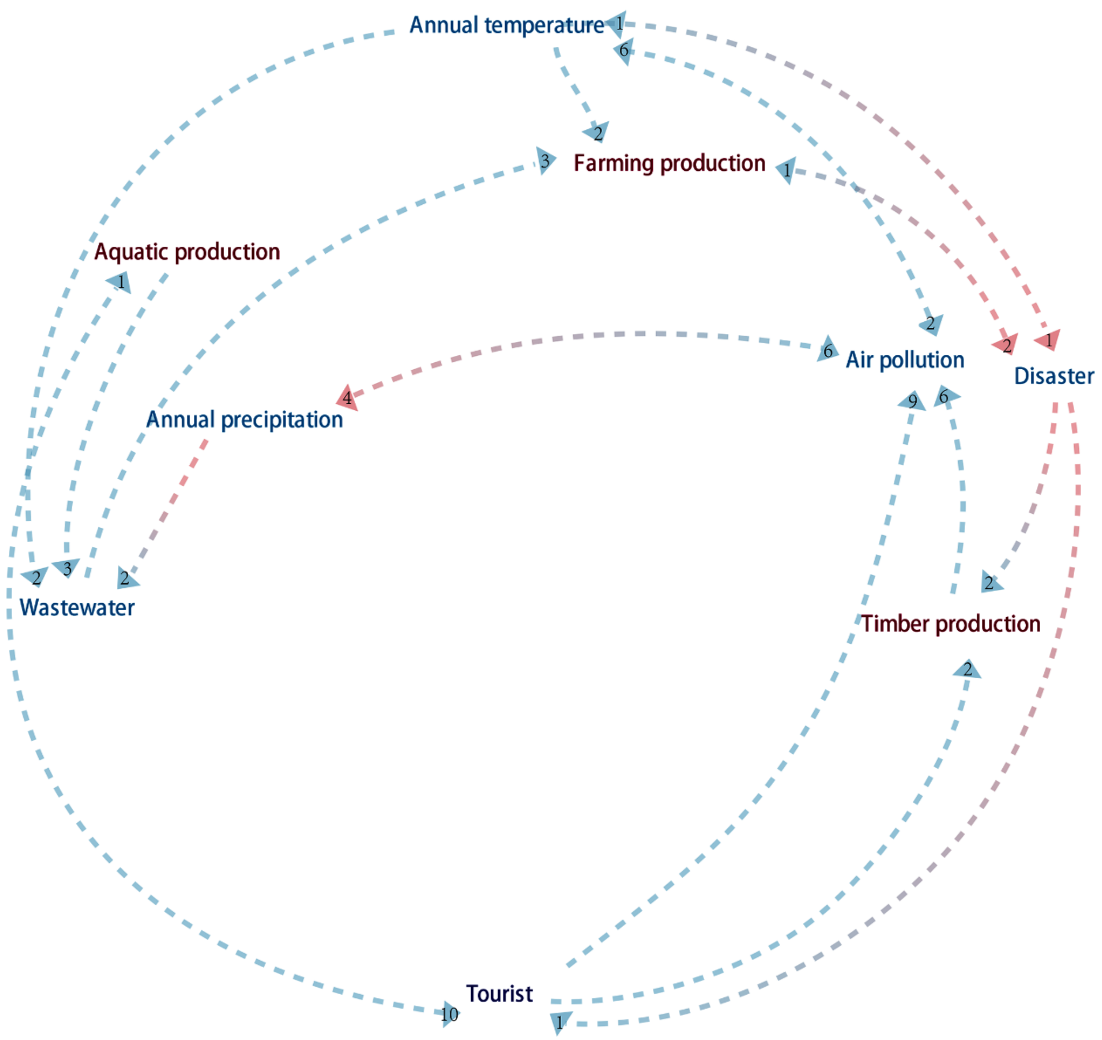


Figure 3.3-9 Causal loop diagram of coevolution of ES. Blue represents an increase in this variable and red represents a decrease in the variable. In the feedback loop, if the arrow colors are all monochromatic, it represents positive feedback, and if there is a transition in the arrow color, the feedback is balanced feedback. Numbers imply causal effect delayed response years.

3.3.3 System connectedness and stability

In Figure 3.3-10, this study analysed the reasons behind the fluctuation of the system stability in provisioning (farming and aquatic production) and regulating services (annual temperature and rainfall). Connectivity analysis suggests that under the control of the planned economy (in 1955-1980), human activity was the main driver of the higher risk of system failure. China carried out a lot of land reclamation to solve hunger, which has caused huge ecological degradation. The single crop and low yield have made farmers do more land reclamation to meet livelihoods, coupled with severe climate impact, the connectivity grew rapidly. From 1980 to 1990, the risk of systemic failure increased due to the stress of land management due to labour outflows. Land reform made rural labour no longer mandatory to do farm work; reform and opening up the market economy have created high-paying jobs in the cities that have attracted an exodus of rural labourers. From 1990 to 2005, China's economy took off due to the rapid growth of business investment brought about by the reform and opening up (in 1978) and accession to the WTO (in 2001). With the increasing maturity of vegetable greenhouses and aquaculture technologies, multi-type supply exploration has increased the heterogeneity of provisioning services, and mature technologies have weakened the connectivity between provisioning services and climate change. In addition to the support of comfortable climate conditions (climate warming, stable precipitation), the system connectivity decreases rapidly. Coupled with accession to the WTO in 2001, international trade allowed provisioning services to explore more diverse supply needs, and system connectivity reached its lowest point (in 2005). After 2005, with the influence of trade globalization and local market competition, the provisioning service began the trend of intensification and industrialization, homogenized. Coupled with cropland loss and abandonment, this increased provisioning pressures on land. Under growing climate variability (decreasing precipitation and increasing temperature fluctuation), the system showed signs of resilience erosion and instability during 2005 to 2010.

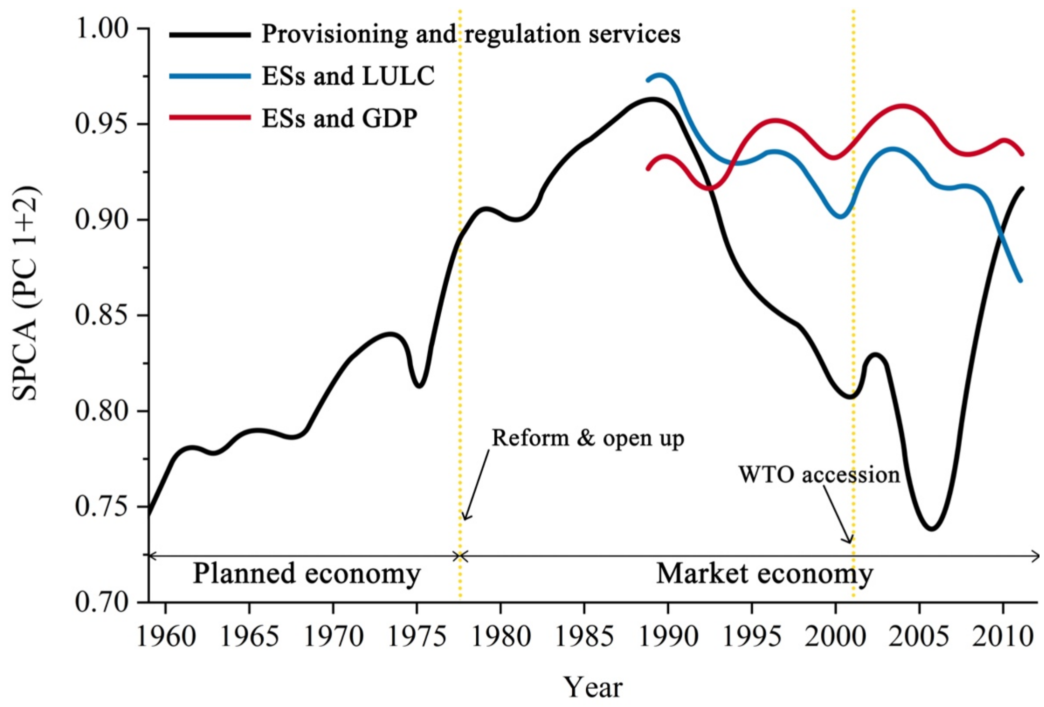


Figure 3.3-10 Connectivity of ES sector with LULC and GDP in Shandong Province from 1950 to 2022. The three curves represent the connectivity of individual regulating and provisioning of service records (black lines) and of all ES metrics with LULC (blue lines) and ES with GDP (red lines). These curves were calculated as the proportion of variability (eigenvalues) of PCA axes 1 and 2 over a 20-year moving window.

The connectivity of the ES and LULC has been on a steady downward trend. Between 1990 and 2000, the implementation of a large-scale reforestation policy converted previously abandoned grasslands and shrubs in mountainous areas into forested land, which led to a rapid decline in soil erosion, a decrease in connectivity, and a reduction in the risk to the system. Afforestation continued steadily over the next decade, but the system failures began to intensify with urban expansion, gradual encroachment of unused land and grassland, growth in carbon and sewage emissions, and continued rising demand for provisioning services. Government regulation of carbon emissions and sewage treatment then began between 2005 and 2013, and the capacity for provisioning services gradually levelled off at a high level, and system risks began to ease.

However, the connectivity of ES to GDP has always fluctuated steadily with small increases, and connectivity has always been high. This suggests that economic development over the past 40 years has consistently kept ecosystems at high risk and has not seen a tipping point approaching(Dearing et al., 2014b).

Overall, Shandong's socio-ecological system has transitioned from an agriculture-dominated to an urban-driven regime. Connectivity between provisioning and regulating services first declined with technological advances but rose again with urban expansion and increasing climate variability, indicating continuous weakening of social-ecological resilience. Urban expansion triggered natural land loss and landscape homogenization, reducing ecosystem adaptability and responsiveness. Although governmental interventions strengthened carbon and wastewater management and stabilized provisioning capacities, the high dependency of economic growth on ecosystem services persisted, suggesting an approach toward a potential critical transition in future.

3.4 Discussion

3.4.1 Summary of the co-evolution of ES and LULC

Firstly, this study summarized the trends of ES and LULC. In terms of ES, since the 1980s, regulating services such as climate regulation and pollution have deteriorated, and provisioning services and cultural services represented by tourist numbers have risen along with GDP. Regarding LULC, from 1985 to 2021, when the total land area is 100%, the area of urban land (from 11% to 23%), forest land and water expanded, while all other land areas, represented by agricultural land (from 80% to 68%), declined significantly, which is consistent with previous studies (Zheng & Li, 2022; Zheng & Zheng, 2023a; Zhu et al., 2022).

Second, this study constructed the conceptual model through the Granger causality test and found the causality relationship between LULC and ES (Figure 3.3-7). Our analysis of LULC (Figure 3.3-4) illustrates that urban expansion is the main driver of land use change. Urban expansion promotes the growth of forests and water lands, but encroachs on cropland, shrublands, grasslands, wetlands and barren lands, leading to fragmentation and irreversible degradation of these lands (Zheng & Li, 2022). The increase of forest land and water bodies benefits from the implementation of ecological protection policies. There has been a rapid increase in forest land, mainly due to the afforestation of abandoned farmland and barren mountain project implemented by the government in the hilly area of south-central Shandong Province, also due to the construction of key forestry protection zones along the coast (Ren et al., 2023). The increase in water area is mainly contributed by barren land, shrubs, and urban land, mainly due to the implementation of government measures such as the establishment of the Yellow River Delta National Nature Reserve (1992) and ecological governance of riverbank lakes (Liu et al., 2014, 2018). In addition, ES and LULC have evolved in a coordinated or balanced way in the past 40 years (Figure 3.3-8). Urbanization increases the demand for supply services (farming, aquatic and timber production) and worsens key regulatory services (wastewater and carbon emissions), showing a synergistic relationship with tourism. Wetland degradation is a trade-off with rising temperatures and fisheries, and it also exacerbates the decline in precipitation. The lack of precipitation has led to the loss of grass and shrubs. The increase in tourists had a trade-off effect with barren land, shrub, grassland and wetland, and co-evolved with construction land and forest land.

Thirdly, our study reveals the results of the EKC analysis and the stability of the system. Economic growth is responsible for the accelerated destruction of ecosystems in China's coastal provinces (He et al., 2014). The EKC model (Figure 3.3-4 and Figure 3.3-5) shows that over the past 40 to 60 years, very low incomes have led to dramatic changes/degradation of the environment until a certain level of economic development is reached (Stern et al., 1996). Our study shows that low incomes of less than 10,000 Yuan have caused dramatic degradation of some land types (especially agricultural land, grasslands, and wetlands), while poverty drives urbanization and policies for ecological conservation force the expansion of forestland and water bodies. As GDP growth continues, urbanization is still on the rise, which will pose further challenges to the capacity of ESs in the future (Gross & Ouyang, 2021; Hossain et al., 2017). Thus, although higher income stages alleviate some environmental pressures, the long-term sustainability of SES functions remains uncertain. Moreover, the critical point of regulating and supporting service over capacity brought by economic development and the threshold of safe operation space still needs to be further predicted (Dearing et al., 2015).

In terms of system stability in Shandong Province, the link between increasing provisioning services and slowly deteriorating driving variables (temperature, precipitation) gradually weakens. Before 1990, climate-dependent agricultural patterns made drought a driver of systemic resilience and instability (El-Bilali et al., 2020; Zhang et al., 2015). Subsequently, the effect of the slow variable on system failure is gradually weakening, as it is supported by agricultural technology (vegetable greenhouse technology, agricultural drip irrigation, and aquaculture technology (after 1990)). Moreover, since China's accession to the WTO in 2001, intensified agricultural production under trade globalization has expanded provisioning services (e.g., agricultural yield) but simultaneously led to significant declines in key regulating services (e.g., water and climate regulation), reflecting a clear dynamic trade-off driven by socioeconomic transformation (Lin et al., 2019; Tu et al., 2019).

From 1980 to 2022, the connectivity between economic growth and ecosystem services increased gradually before stabilizing at a high level. This intensified connectivity suggests a growing reliance of economic sectors (e.g., agriculture, industry, tourism) on ecosystem services (e.g., water supply) and likely reflects the influence of eco-friendly practices and policies (e.g., green economy strategies, eco-compensation schemes, environmental regulations).

Over the past 40 years, system connectivity between ES and LULC has sharply declined, suggesting reduced ecosystem sensitivity and responsiveness, likely due to LULC-driven ecosystem degradation or long-term damage (e.g., to habitat quality and climate regulation), which has weakened ecosystem resilience. Rather than signalling immediate collapse, these changes suggest that the SES may be experiencing a phase of functional disturbance and potential reorganization (Lin et al., 2019, 2024). Nevertheless, continued degradation could eventually cross critical thresholds (Dearing et al., 2014), triggering irreversible impacts on LULC patterns. Thus, identifying and predicting the safe and just operating space for land use and ecosystems is essential for sustaining long-term regional resilience (Dearing et al., 2014).

3.4.2 Policy Recommendations

According to the causal conceptual model analysis, urban expansion and environmental protection policies are the main driving forces of ES change in Shandong Province (Ren et al., 2023; Song et al., 2015). Over the past 40 years, urban expansion has encroached on a large amount of arable land, wetlands, and grasslands, resulting in homogenization and fragmentation of land use types. The growth of cities is also demanding more supply services from ecosystems and degrading regulating services, which increases land degradation and endangers food security and sustainable ecosystem development. The endless expansion of urban areas in Shandong Province is required to control the red line of arable land, ensure food security, and reduce greenhouse gas and sewage emissions for sustainable ecosystem development.

The powerful ecological purification function of wetlands can increase climate stability, effectively control floods and prevent soil desertification (Wang et al., 2010; Yim et al., 2018). However, the causality and balance feedback loop shows the area of wetlands was rapidly declining, water quality was declining, and biodiversity was being lost since 1995 (Yu et al., 2021), as a result of water cover expansion, water pollution, and urbanization. The loss of wetlands leads to higher temperatures and less precipitation, which leads to more sewage, and more water surface that exacerbates wetland loss. Therefore, it is necessary to strengthen environmental pollution control, carry out wetland ecological protection and restoration, establish wetland ecological protection areas, hold the wetland red line, and establish a natural disaster early warning system.

To enhance system stability and resilience, it is crucial to rigorously enforce land use management policies, uphold the farmland protection boundary, and prevent excessive urban expansion and farmland abandonment (Li et al., 2018; Xu et al., 2019). The government should focus on diversifying industries, advancing agricultural assistance programs, and promoting green agriculture and ecotourism. Implementing varied ecological compensation mechanisms and creating diverse employment opportunities will help attract labor back to rural areas. These measures are essential for achieving a balanced approach to ecological security and rural revitalization in Shandong and other regions in China (Liu et al., 2023).

3.4.3 Limitations and future improvements

In analysing the co-evolutionary relationship between ES and LULC in the time series, this study only focused on temporal data and did not account for spatial-scale effects. Biological ES (e.g., primary production, water quality, biodiversity) were not included due to the lack of consistent, long-term, and spatially explicit data, particularly before 1985. This limitation may affect the validation of Granger causality results and the robustness of inferred feedback. Moreover, research results lack intuitive mapping and regional guidance. Future research should incorporate biological ES indicators and high-resolution spatial data to refine the assessment of system resilience and define safe and just operating spaces across diverse landscapes. Caution is also needed when interpreting system stability due to limited comparability with other SES.

Our empirical results reveal the co-evolutionary relationship between ES and LULC, which is helpful to further understand the operation and evolution trend of a complex social ecosystem, and provide suggestions for ecosystem management in Shandong Province. The results will also provide multi-dimensional scientific support for Sustainable Development Goals (11- sustainable cities, 15-life on land, 16-peace, justice & strong Institutions) and research on complex social ecosystems in other similar mountainous and coastal SES in China and beyond.

3.5 Conclusions

We use decades of time-series analyses based on official provincial statistics to study SES and construct a conceptual model of the relationship between ES and LULC. In Shandong, these analyses provide provincial-level evidence that the long-term dynamics of regional LULC and ecological systems have become very unstable since 2005, and that tipping points may occur in the near future. This instability is likely due to ecosystem degradation caused by uncontrolled land use (urbanization and farming land loss), which has reduced ecosystem resilience.

There is evidence that urban sprawl is taking all of the natural land except water and forest, especially agricultural land, with serious implications for food security. As the economy grows, urban expansion will continue with no tipping point in sight. Urbanization increases demand for provisioning services and degrades key regulating services, in synergy with tourism. Wetland loss reduces annual precipitation and increases temperature, creating balance feedback with temperature and rainfall, and drought leads to a reduction in shrubs and grasslands. Ultimately, all these impactors caused a decline in the region's resilience.

The outcomes support the necessity of grasping and devising development strategies based on an understanding of social and ecological relationships, connectivity constraint boundaries and dynamics of systems.

Chapter 4 *Modelling social-ecological systems of land use and ecosystem services co-evolution in Shandong of China*

Climate change and LULC transitions are increasingly destabilizing ecosystem services (ESs), especially in regions facing compounded resource and socio-economic pressures. However, existing studies rarely integrate multiple socio-economic and climatic drivers to quantitatively unravel the coupled mechanisms and dynamic trajectories of ES-LULC co-evolution at a regional scale. To evaluate the coupled dynamics between ESs and land use (LULC) under climate, demographic, and economic stressors, this study developed a socio-ecological system dynamics model and applied it to Shandong Province, China. The model simulates a wide range of climate scenarios (temperature increase of 1.5-5.7°C; precipitation change from -70% to +50%), combined with urbanization, cropland management, afforestation, water-use strategies, and population-economic pathways (SSP 1-5). It tracks the long-term trajectories of seven ESs and seven LULC categories. Results show that (1) under extreme warming and drought, all ESs collapse simultaneously, with water bodies disappearing by 2050, signalling a systemic tipping point; (2) water-saving strategies can delay water collapse by up to 30 years, highlighting adaptive potential; (3) urbanization accelerates built-up land expansion at the cost of natural ecosystems; cropland management improves food production and carbon storage; afforestation enhances carbon and aesthetic services but reduces water yield; (4) SSP3-5, featuring population growth, inequality, and fossil-driven development, further exacerbate long-term ES degradation. Findings underscore the need for integrated land-water-carbon governance. Priorities include farmland protection, ecological reuse of urban land, ecological flow allocation, and dual carbon control. To prevent irreversible shifts, global warming must be limited to 2 °C. The model is transferable to other mountainous and coastal areas under similar stress conditions.

4.1 Introduction

4.1.1 Background overview

Approximately one-third of the global land cover has been altered by human activities over the past 60 years. Recent assessments further suggest that the magnitude of global land use changes is four times greater than earlier long-term estimates, with substantial implications for ecological, environmental, economic, and social systems across scales (Radwan et al., 2021; Winkler et al., 2021). Population, economy, and climate change are the driving forces behind land change. As economies boomed after World War II, the global population has grown from 2.5 billion in 1950 to nearly 8.2 billion in 2024 (United Nations, 2024), steepening agricultural supply pressures have expanded the global agricultural area (i.e., farmland and rangeland / pastureland) by 1 million km^2 and 0.9 million km^2, respectively. Expansion of construction land and agricultural production has accelerated the fragmentation and loss of ecologically sensitive areas (grasslands, forests, wetlands, water covered land). For instance, forests globally have suffered a net loss of 0.8 million km^2 (Fang et al., 2022b; Winkler et al., 2021). Extreme weather events (droughts, floods, wildfires) brought on by a warming climate also accelerate land degradation (Salimi et al., 2021). The concession of natural land cover to human demands causes irreversible land degradation and serious challenges to ecosystem services (ES) (e.g., reduced carbon storage capacity, soil erosion, biodiversity degradation, weakened water regulation, food security risks, etc.) (Boakes et al., 2024; Cabernard et al., 2024; Wu et al., 2024; Yuan et al., 2024). The global loss of ESs is estimated at \$44 trillion, with irreversible land degradation directly affecting nearly half of the global population (Esch et al., 2022). This indicates that land degradation has dire impacts on ecosystems, socio-economic systems, while protecting, restoring and promoting the sustainable use of terrestrial ecosystems is one of the overarching objectives of the United Nations Sustainable Development Goal (SDG 15). The economic impact of ecosystem collapse is expected to increase in the coming years. A new World Bank report estimates that the collapse of specific ESs supplied by nature could lead to an annual decline in global GDP of \$2.7 trillion by 2030 (World Bank, 2021). Of these, low-income countries whose economies are heavily reliant on natural assets are the hardest hit — for example,sub-Saharan Africa and South Asia, where real GDP would shrink by 9.7% and 6.5% annually(Johnson et al., 2021). Therefore, concerted efforts from researchers, policymakers and practitioners are essential to address the ESs and socio-economic challenges arising from LULC change.

4.1.2 Current challenges

Land use and ecological health are intrinsically connected (Fu et al., 2015b), constituting a nexus between sectors or issues (Estoque, 2023). This study defines the ecosystem service and land use/ land cover nexus (ES-LULC nexus) as a concept that elucidates the intricate interrelations, including trade-offs, between land use and ESs. Land use is primarily influenced by population, economic, and climatic changes (Stehfest et al., 2019). The encroachment of land cover due to human activities, such as the expansion of urban and farmlands into natural landscapes, leads to irreversible degradation of natural land (Eswaran et al., 2019). This degradation jeopardizes the ecosystem's provisioning services (food, water, timber), regulating services (climate, pollution, disaster management), supporting services (habitat, soil protection), and cultural services (aesthetic, tourism, heritage) (MEA, 2005), while also undermining the stability of socio-economic systems. As ecosystems destabilize, the diminishing monetary and non-monetary values of essential ESs draw increased attention from researchers, who utilize ecosystem service assessments to aid policymakers in formulating sustainable land use and environmental management strategies to address ecological issues (Fürst et al., 2017; Goldstein et al., 2012). For example, the land use scenario simulation of Sichuan-Yunnan ecological barrier provides a new way for land use planning of ecological functional areas (Li et al., 2021); Li et al. (2021) found that large-scale afforestation policies had a long-term positive impact on soil erosion and sandstorm control in semi-arid China.

The ES-LULC nexus is characterised by its intrinsic complexity including feedback, non-linear processes, which means that the relationship between land use and ESs isnot straightforward (Fürst et al., 2017). One example is urban expansion, which reduces cropland and pressures food provision, but where advances in agricultural technology and disaster management have increased farmland net ecosystem productivity, mitigating much of the pressure on food security (Zhang et al., 2024;

Garibaldi et al., 2017; Guo et al., 2019). This stabilisation of supply reduces the need to retain all agricultural land, enabling conversion to urban or ecological uses (Grain to Green project); in turn, changes in cropland area influence subsequent management strategies, creating a bidirectional feedback within the ES-LULC system. These feedbacks highlight the need to understand the complex relationships and dynamic behaviour of ES-LULC nexus to support long-term sustainable management policies.

The complex drivers of LULC change are deeply intertwined with the needs of social systems (Stehfest et al., 2019), extending the ES-LULC nexus beyond simple 'land-environment' interactions to encompass climate, demographic, socioeconomic, and global political realms. This complex coupling reflects the deep integration of natural and social systems and their dynamic interactions. Therefore, an integrated and dynamic approach that focuses equally on natural and social systems is essential to understanding this linkage. The nexus research approach is often used to analyse the dependencies (trade-offs and synergies) between sectors or issues in order to develop sustainable policies (Berrio-Giraldo et al., 2021). However, its ability to balance natural and social systems remains questionable due to the lack of a harmonised framework (Stringer et al., 2018), the Social-Ecological Systems (SES) approach explicitly fills this gap (Gomez-Jaramillo et al., 2024; Wang, et al., 2023). The SES approach provides a unifying framework for understanding the coevolution of LULC and ESs. As an interdisciplinary perspective, SES embeds humans within ecosystems and highlights the coupled interactions of social and ecological processes.including feedback, non-linearities, and delays that determine the overall dynamics of the system. This framework moves beyond the traditional “nature–society” dichotomy and offers a basis for analysing complex system features such as feedbacks, non-linearities, and critical thresholds (Biggs et al., 2021). The importance of SES lies in its ability to systematically reveal long-term trajectories and thresholds in human–nature interactions. Recent studies illustrate how SES perspectives uncover systemic dynamics across contexts. In Bangladesh, SES modelling revealed that warming combined with upstream withdrawals and political instability could reduce food security by more than half, underscoring the vulnerability of coupled water–food systems (Roy et al., 2024). In China’s karst region, large-scale ecological restoration not only boosted biomass and carbon sequestration but also catalysed livelihood transitions beyond farming, linking ecological recovery to social transformation (Qiu et al., 2022). In the UK uplands, integrating land managers' behavioural choices with spatial system dynamics demonstrated how policy incentives propagate through landscapes to reshape long-term vegetation patterns (Termansen et al., 2019). Taken together, these cases show that SES approaches move beyond sector-focused analyses to reveal feedbacks, thresholds, and cross-scale linkages. This perspective deepens our understanding of ES-LULCcoevolution and supports the design of adaptive land policies that strengthen socio-ecological resilience.

4.1.3 Research gap

Numerous studies have examined the effects of land use on ESs (Liu et al., 2021; Mekuria et al., 2023; Roy et al., 2024; Wu et al., 2020), and it is broadly acknowledged that prevalent research methodologies in the world, the InVEST model (Grafius et al., 2016; Jiang et al., 2023b), the Value Equivalent Approach (Song & Deng, 2017; Wang et al., 2023), and various bio-physical models of ESs (Duan et al., 2021; Huang et al., 2019), possess intrinsic limitations in accurately representing the complexities (e.g., feedback loops, non-linearities) between social and ecological variables. For example, both the InVEST model and the Value Equivalent Approach assess alterations in ESs based on satellite map or LULC statistics, and bio-physical modelling of ESs typically is rooted in physical variables (e.g., soil, water); however, neither valuation method sufficiently incorporates social factors (Li et al., 2020; Wang et al., 2018). Consequently, current scholars have underscored the integration of ecological (essential ESs) and social (e.g., economic prosperity, demographic, cultural, policy, etc.) variables in discerning the potential effects of land use on ESs (Qiu et al., 2022; Ratnayake et al., 2024).

Although researchers have emphasised that social factors (population, GDP expansion) drive changes in coupled ES-LULC, quantitative studies of socio-natural system dynamics are limited (Li et al., 2024). Most studies explore ES-LULC issues from an ecological perspective, mainly using quantitative research methods such as bio-physical models or value transfer method, with limited applications of other methods (e.g., interviews, questionnaires, causal analyses, expert analyses). While a few studies have employed SES approaches, none of them has explored the correlation between land use-ESs through a conceptual SES framework that integrates socio-ecological components and factors (Liu et al., 2015; Zhang et al., 2023). For instance, Bennett et al. (2015) used causal loop diagrams to develop a framework for ecoSERVICES that examines the three primary challenges of biodiversity, environmental services, and human well-being; Peng et al. (2023) linked ESs, ecosystem vulnerability, and social vulnerability using the SES vulnerability cascade framework. Overall, the review suggests that the SES approach has not been explored in the study of ES-LULC nexus.

4.1.4 Research Objectives

To address the identified research gap, this study is the first attempt to use the SES approach to investigate the relationship between land use change and ESs of Shandong, while considering both social and ecological systems and their complex interactions. Specifically, this study employ the system dynamic model to quantify the dynamic interactions between social and ecological variables. The purpose of this study was to understand the SES relationship between land use, ESs and population and GDP in Shandong Province, China. To achieve the purpose of this study, this study proposes the following research questions:

1. How are social and ecological variables interrelated to determine the dynamic behavior of the system?
2. How does the ES-LULC nexus perform under different socio-economic policies and climate scenarios?

This study aims to serve as an informative tool for academics and policymakers on the long-term interactions between land use and ESs, facilitating sustainable management of land and ecosystems amidst varying socio-economic policies and climate change.

This chapter is arranged as outlined below. Section 2 shows rationale for the selection of the study site; followed by Section 3, which presents the methodologies for developing and validating the conceptual and empirical SD model; Section 4 delineates the results derived from the SD model of the ES-LULC nexus and the scenario analysis; Section 5 examines the principal findings and policy implications;

while Section 6 concludes the essential insights of the study, its prospects, and potential limitations.

4.2 Study area

China has experienced some of the most dramatic LULC changes globally over the past three decades, driven by rapid economic and population growth (Miao et al., 2016; Winkler et al., 2021). Simultaneously, China has emerged as a key contributor to global ESs, accounting for 25% of the world's new green vegetation over the past 20 years (Liao et al., 2024) and leading the global transition to clean energy (Song et al., 2024). These rapid changes position China as an exemplary region for studying the ES-LULC nexus, offering a critical lens through which to explore the dynamics of SES evolution. In addition, SES modelling necessitates extensive multi-scale social and ecological data support.

Shandong Province, located along China's eastern coast, spans an area of 157,900 km^2 and possesses unique socio-economic and environmental characteristics, making it a critical region for studying the ES-LULC nexus (Figure 4.2-1). As China's second most populous province (with a population exceeding 100 million) (*China Statistical Yearbook*, 2023) and its third-largest economy (GDP of 4,667.7 billion RMB in 2023), Shandong's highly concentrated economic activities and large population emphasize the intricate interactions between land use and ESs. Furthermore, Shandong is the largest producer of vegetables (92 million tons in 2023) and aquatic products (9.14 million tons) in China, playing a pivotal role in national food security while supporting the livelihoods of over 20 neighbouring countries (*Shandong Statistical Yearbook*, 2023). These economic activities generate significant spillover effects on regional and neighbouring ecosystems, making Shandong's ESs vital for both national ecological security and regional well-being. The province's distinctive climatic conditions further amplify these dynamics. Shandong's warm temperate monsoonal climate is characterized by highly concentrated precipitation (over 50% occurring in summer) and frequent droughts in spring and autumn (*Shandong Statistical Yearbook*, 2023). These environmental factors exacerbate pressures on land use and ESs, shaping a complex socio-ecological system. Over the past few decades, Shandong's urbanization rate has increased rapidly, rising from 13% in 1985 to 66%

in 2023. Urban expansion, coupled with policy-driven land use reforms such as reforestation, has significantly altered land use patterns. These changes have intensified land degradation and fragmentation, profoundly impacting the structure and function of regional ecosystems (Fan & Xiao, 2020; Ren et al., 2023). These distinctive socio-economic and environmental dynamics make Shandong an ideal case for investigating the ES-LULC nexus within a socio-ecological framework.

Moreover, Shandong offers notable practical advantages for research. Shandong's relatively high data transparency, combined with the research team's familiarity with the province's data environment, facilitates effective communication with local statistical departments and government agencies. This ensures access to reliable datasets and enhances the scientific rigor of the modelling process.

Thus, Shandong province is not only a representative and exemplary case for exploring the ES-LULC nexus but also a critical region whose findings can inform ecosystem management and policymaking in similar socio-ecological contexts globally.

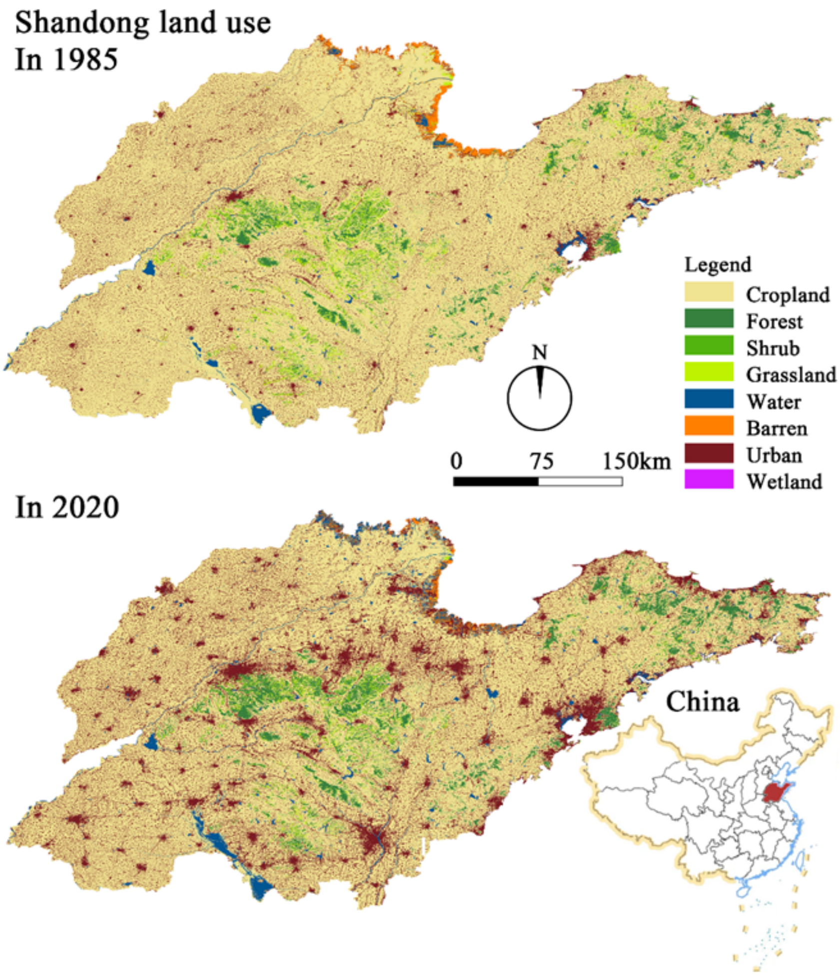


Figure 4.2-1 The location and land use of Shandong province of China.

4.3 Methodology

This study adopts a System Dynamics (SD) Modelling approach, hereafter termed the ES-LULC nexus Socio-Ecological System model (LULCESN-SES model), to examine the socio-ecological dynamics within the ES-LULC nexus. The SDM approach was chosen for its capability to model complex SES, enabling the integration of social and ecological variables to capture feedback mechanisms, non-linear relationships, and time delays (Ford, 2010; Hossain et al., 2020). Initially developed by Forrester (1961), SDM has been extensively applied in fields such as industrial economics, environmental systems, and population dynamics (Sterman, 2000). In recent years, its application has expanded to diverse SES contexts, including agricultural systems (e.g., Bastan et al., 2017), dynamic change of land use and social-ecosystem (e.g., Berrio-Giraldo et al., 2021; Zhang et al., 2023), and the interconnected security of water, food, and energy resources(e.g., Naderi et al., 2021). The methodological framework and procedural steps employed in this study are detailed in Figure 4.3-1.

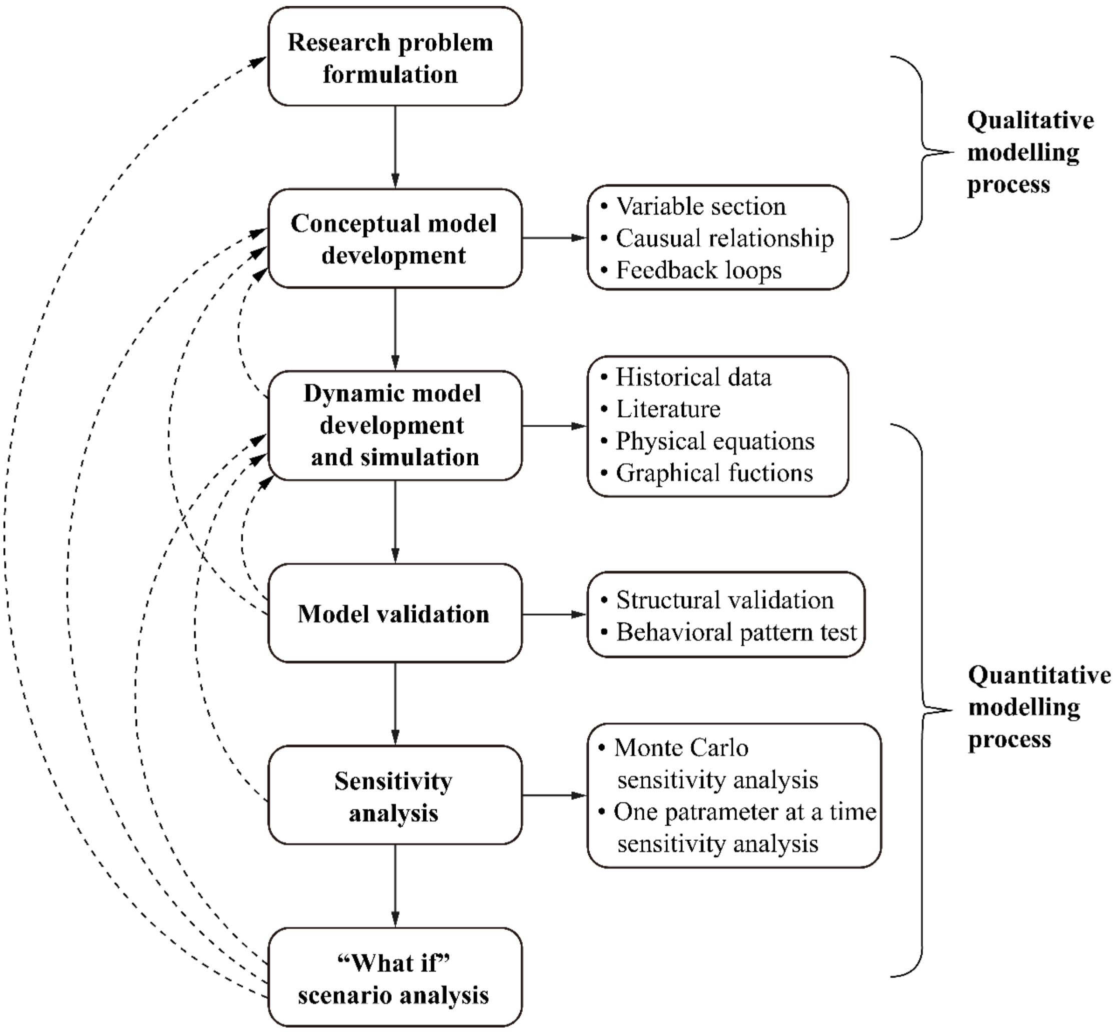


Figure 4.3-1 The methodological framework implemented in this study aligns with the principles outlined by Maani and Cavana (2007) and Sterman (2000), ensuring a systematic approach to modelling socio-ecological dynamics (Roy et al., 2024).

4.3.1 Conceptual model development

The process begins with the development of a conceptual model, referred to as a causal loop diagram (CLD), which outlines the system's structural relationships (Hossain et al., 2020; Roy et al., 2024). In a CLD, variables are linked by directional arrows, each annotated with a positive (+) or negative (−) sign. A positive sign signifies that a change in one variable leads to a corresponding change in the same direction for the connected variable. In contrast, a negative sign implies that a change in one variable results in an opposite change in the linked variable (Haraldsson, 2004). These causal interactions form feedback loops, which are categorized as either reinforcing (positive) or balancing (negative) loops (Berrio-Giraldo et al., 2021). Reinforcing loops drive exponential growth or decline, often leading to system instability, while balancing loops counteract changes, promoting stability and equilibrium (Hossain et al., 2020).

This study developed a conceptual SES model to explore the relationship between ESs and land use in Shandong, China (Figure 4.3-2). The model variables and the complex interactions between social and ecological components were identified based on a systematic review of prior studies, relevant literature, and findings from preliminary research. The conceptual model comprises 28 system variables interconnected by 42 causal links. Within the model, a total of 10 feedback loops were identified, including 2 reinforcing loops and 8 balancing loops. This section discusses the significance of key feedback loops in shaping the structural dynamics of the ES-LULC nexus (Table 6.3-1).

Feedback loops B1, B2, and B3 illustrate the dynamic interactions between construction land and farmland (B1), barren land (B2), and grassland (B3), respectively. In these loops, an expansion of construction land leads to a reduction in the areas of farmland, barren land, and grassland, while a decrease in construction land would conversely allow for the recovery or expansion of these land types.

Population increase contributes to farmland reduction through multiple pathways and ultimately to a decrease in population as a result of economic development. In particular, the urbanization driven by population growth exacerbates agricultural labor shortages, resulting in farmland abandonment and reduction (B4); simultaneously, the expansion of construction land directly encroaches upon farmland (B5) and indirectly threatens farmland security by reducing water yield (B6); moreover, construction land expansion intensifies carbon emissions, prompting carbon neutrality policies that accelerate cropland-to-forest conversion (B7); the multifaceted loss of farmland has not prevented an increase in farming production (as economic development in R1 promotes agricultural inputs/technology and agricultural production growth, finally drives economic growth), which increases the agrarian economy and total GDP, this economic growth ultimately reduces fertility intentions and birth rates, leading to a decline in population (B4, B5, B6, B7).

Additionally, feedback loop B8 indicates that population-driven urban expansion and farmland loss contribute to the gradual forestland expansion. The increase in forest cover enhances landscape aesthetics (tourism value) which in turn promotes the expansion of water covered land (as demonstrated by R2, where water body and landscape aesthetics reinforce each other). This expansion creates a favourable environment for increased fisheries production, further stimulating agricultural output and overall GDP growth. However, the economic growth resulting from these processes ultimately reduces fertility intentions, leading to a decline in population.

This conceptual SES model serves as the foundation for developing the simulation model in the next stage. A summary of the feedback loops is presented in Table 6.3-1.

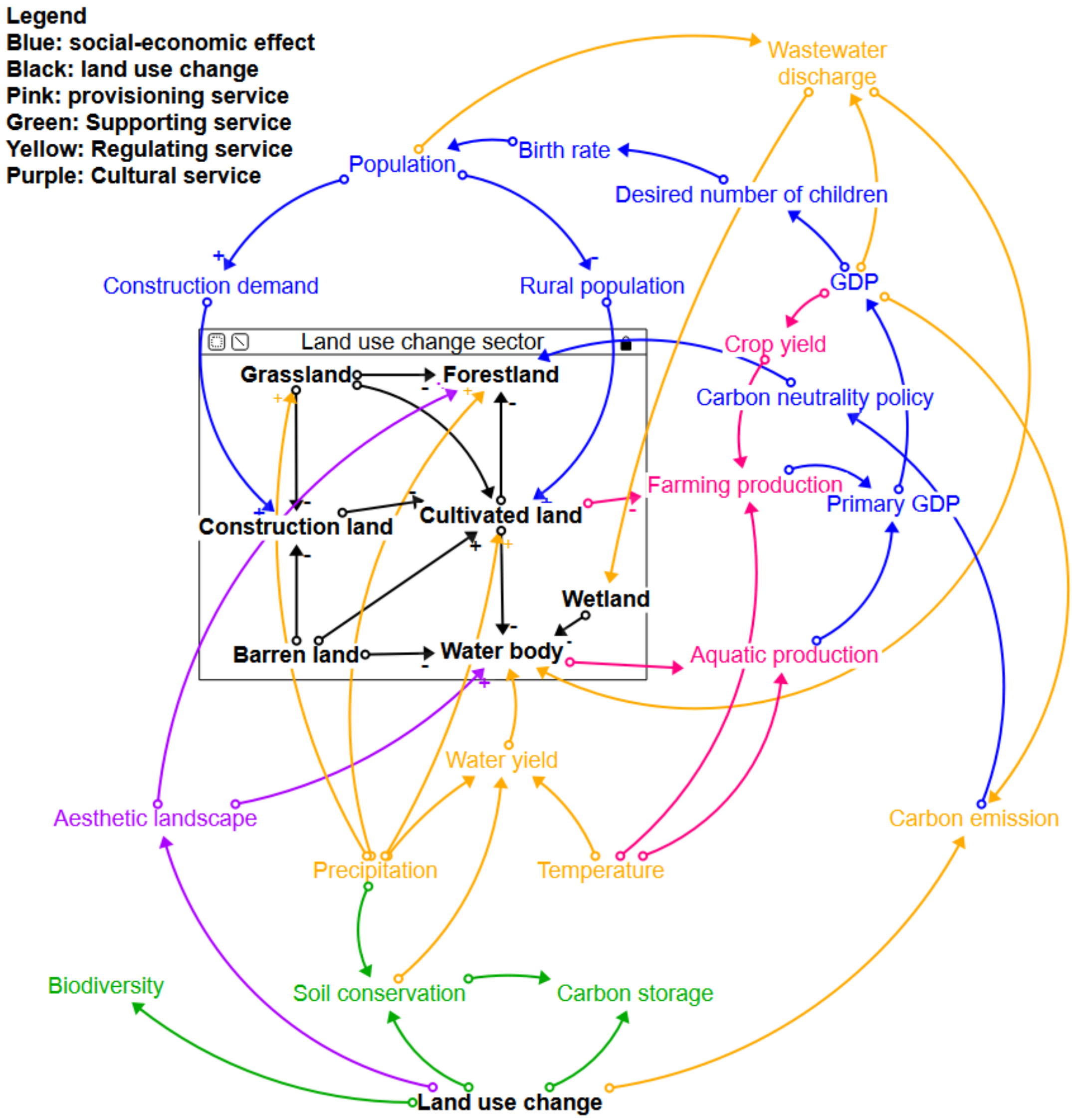


Figure 4.3-2 Conceptual SES model of the ES-LULC nexus.

4.3.2 Model formulation, input data and parameterisation

This study builds upon the conceptual SES model by constructing a Stock-Flow Diagram (SFD) in STELLA Professional v.3.1 (https://www.iseesystems.com) to simulate system dynamics. While the conceptual model effectively represents causal relationships and feedback mechanisms among variables, its qualitative nature limits its ability to capture temporal system evolution. To address this limitation, the SFD was developed based on physical equations and incorporates both quantitative and qualitative data to enhance the accuracy of dynamic system analysis. The SFD consists of three fundamental components: stocks (accumulations), flows (rates), and converters (auxiliary variables), which interact to form feedback loops that drive system evolution (Ford, 2010). Stocks represent accumulated resources within the system, such as total farmland area or GDP. Flows indicate the rate of change in stocks, including the expansion and reduction of forest land or population growth and decline. Converters function as auxiliary variables that regulate flow rates, for instance, birth and death rates influence the total population increase and loss within a given period (Roy et al., 2024). Within the SFD, converters indirectly shape system evolution by regulating flow magnitudes, while flows determine the accumulation or depletion of stocks.These dynamic interactions establish feedback mechanisms that critically shape system behaviour and evolutionary patterns (Pham et al., 2021). For example, in the LULC module, farmland, forest land, grassland, barren land, and water-covered land are defined as stocks; their conversions such as afforestation, deforestation, and urban expansion are represented as flows; while population demand, climatic factors, and transfer years act as converters. This structural design was consistently applied across other ecosystem service modules, ensuring an integrated representation of the SES.

In this study, the dynamic LULCESN-SES model was constructed using physical equations to define the relationships among SES variables within STELLA Professional v.3.1 (Table 6.3-3). The model employs annual time-step data aggregation to simulate system-wide trends. To ensure accurate parameterisation, an extensive review of relevant literature and datasets was conducted to obtain stock values (initial conditions), converters, and graphical functions. A key challenge in model development was the limited availability of site-specific parameter values. To address this, national and regional datasets (e.g., average water depth, permeability coefficients) were used as proxies to approximate local conditions. Furthermore, due to the absence of long-term empirical data, direct model calibration and prediction were constrained. To overcome these limitations, the study integrated computational formulas from the InVEST model – specifically for carbon storage (Figure 6.3-8), soil retention (6.3-9), and water yield (Figure 6.3-6) – to derive more reliable time-series estimations. To quantify the influence of multiple independent variables on a dependent variable, regression equations were applied. For example, water yield was modelled as a function of water area and unit productivity, enabling the estimation of relationships in the absence of direct observational data. SPSS software was used to perform multiple and linear regression analyses, incorporating sequential time-series data derived from the conceptual model. Additionally, graphical functions, a built-in feature of STELLA software, were utilised to approximate relationships between independent variables when empirical data were unavailable. These functions allow for the definition of nonlinear dynamics (e.g., irrigation effects on crop yield) by selecting from predefined functional forms such as linear, S-shaped, nonlinear, or oscillatory relationships, or by manually adjusting curves based on theoretical assumptions.

To ensure the reliability of the simulation, a diverse range of historical and cross-sectional datasets were integrated to parameterise the model, as detailed below. Data related to population, higher education attainment, fertility intentions, crop and fisheries production, GDP, urbanization rate, surface water availability, and carbon emissions were obtained from the Shandong Statistical Yearbook. Climate variables (e.g., precipitation, temperature) were sourced from the National Meteorological Data Center to compute annual climate trends. Parameters and coefficients for carbon storage, aquatic production, and soil retention were derived from the InVEST model and supplemented by regional studies of Shandong (e.g., Wang et al., 2023; Xu et al., 2024; Zheng & Zheng, 2023). For land use change dynamics, this study utilized a sequential time-series dataset (1985 – 2021) for Shandong Province, obtained from the Landsat-based China Land Cover Dataset (CLCD), produced by Wuhan University (https://zenodo.org/records/8176941). The dataset includes annual LULC raster maps, which were processed in QGIS software to calculate the annual area changes for eight LULC categories: cropland, forest, shrubland, grassland, water covered land, barren land, wetland, and construction land.

4.3.3 Model validation

Model validation is a crucial step to establish the credibility and scientific robustness of the LULCESN-SES model as a policy analysis tool (Senge & Forrester, 1980). As system dynamic models are simplified representations of real-world systems, their validation is not to confirm model 'absolute correctness', but rather to enhance confidence in the structure and behaviour of the model through testing from different time series perspectives (Barlas, 1996; Roy et al., 2024; Sterman, 2002). The LULCESN-SES model was validated by historical datasets (between 1990 – 2020) for the key variables (e.g., land uses). Model calibration is initially conducted using the first subset of historical data (1990 – 2005) to optimize the dynamic equations of key variables, ensuring alignment with observed trends. Subsequently, a second subset (2006 – 2020) was employed for extrapolative validation, assessing the model's ability to reproduce historical patterns independent of the training dataset (Hossain et al., 2017; Roy et al., 2024). The model parameters and structure were optimally adjusted through repeated iterations until it was ensured that the simulation results were dynamically consistent with the historical data.

System dynamics modelling requires both qualitative and quantitative tests to validate the model(Barlas, 1989; Schwaninger & Grösser, 2020). To achieve this, structural validation (examining whether the model structure adequately represents the real-world system) and behavioural validation (assessing whether the model produces acceptable behavioural outcomes) are widely used (Barlas, 1989). Structural validation checks the logical consistency of the model, ensuring that its structure is coherent and capable of representing the real system. This can be tested through direct or indirect investigation, using empirical data or theoretical reasoning (Barlas, 1989; Schwaninger & Grösser, 2020). For quantitative validation, this study applies parameter confirmation tests, dimensional consistency tests, and behavioural pattern validation. The parameter confirmation test ensures that the parameters used in the model are meaningful and supported by real-world data or literature (e.g., Ma et al., 2024; Zhao et al., 2023). The dimensional consistency test verifies that all equations in the model adhere to unit balance principles, preventing computational errors caused by unit inconsistencies (Barlas, 1989). These validation steps ensure that the model is not only numerically sound but also theoretically robust, providing a solid foundation for subsequent behavioural validation.

To assess the credibility of model behaviour, this study applies a multidimensional statistical evaluation approach. To determine whether the simulated behavior is reasonable, a multidimensional evaluation matrix is constructed using R^2 (coefficient of determination), PBIAS (percentage bias), RSR (ratio of the root mean square error to the standard deviation of observations), and U_0 (Theil's inequality coefficient). Other studies have also used these tests for model validation (Maleki Tirabadi et al., 2022; Roy et al., 2024; Wu et al., 2013). R^2 measures the goodness of fit between simulated and observed data. Its value ranges from 0 to 1, with values closer to 1 indicating a stronger explanatory power of the model (Wu et al., 2013). PBIAS reflects the systematic deviation of simulated values relative to observed values, indicating whether the model tends to overestimate or underestimate on average. The ideal PBIAS value is 0.0, with positive values indicating underestimation and negative values indicating overestimation (Gupta et al., 1999). RSR (ratio of the root mean square error to the standard deviation of observations) addresses the scale sensitivity issue of traditional RMSE (root mean square error), allowing data with different units to be compared within the same framework (Tirabadi et al., 2022). It is calculated as the ratio of RMSE to the standard deviation of observed data (Equation 4.4). The RSR value ranges from 0 to a larger positive number, with lower RSR values indicating lower RMSE or smaller residual variation. U_0 provides a global assessment of the model's predictive accuracy. Its value ranges from 0 to 1, with values closer to 0 indicating smaller prediction errors (Theil & Nagar, 1961). To further verify the model's dynamic behaviour, this study examines six key variables: crop yield, carbon emissions, built-up area, farmland area, GDP, and population (Figure 4.3-3). The simulated results from 2006 to 2020 are compared with actual observations to ensure that the model accurately captures the long-term evolution of the system (Hossain et al., 2017; Roy et al., 2024). All statistical evaluations follow the standards set by Moriasi et al. (2015), with detailed results provided in Supplementary Table 6.3-2. By integrating structural validation, behavioural validation, and statistical analysis, this study ensures that the model not only reliably replicates past system changes but also has strong predictive power. This provides a robust foundation for scenario simulations and informed decision-making.

$$\text{Coefficient of determination } (R^2) = \left(\frac{Cov(Y_{sim}, Y_{obs})}{\sigma Y_{sim} \sigma Y_{obs}}\right)^2 \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \quad (4.1)$$

$$\text{Percent bias } (PBIAS) = \frac{\sum(Y_{sim} - Y_{obs})}{\sum Y_{obs}} \times 100 \dots\dots\dots \quad (4.2)$$

$$\text{Root mean square error } (RMSE) = \sqrt{\frac{1}{n}\sum_{t-1}^{n} (Y_{sim} - Y_{obs})^2} \dots\dots\dots\dots\dots\dots\dots\dots \quad (4.3)$$

RMSE-observations standard deviation ratio $(RSR) = \frac{RMSE}{\sigma Y_{obs}} \dots \dots \dots \dots \dots \dots \dots \dots (4.4)$

Discrepancy coefficient $(U_0) = \frac{\sqrt{\sum (Y_{sim} - Y_{obs})^2}}{\sqrt{\sum Y_{sim}^2} + \sqrt{\sum Y_{obs}^2}} \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots . (4.5)$

where, Y_{obs} is the observed value; Y_{sim} is simulated value; Cov(Y_{sim}, Y_{obs}) is the covariance of values with respect to the observed or simulated values; and σY_{sim} and σY_{obs} are the standard deviations of the two sets of values.

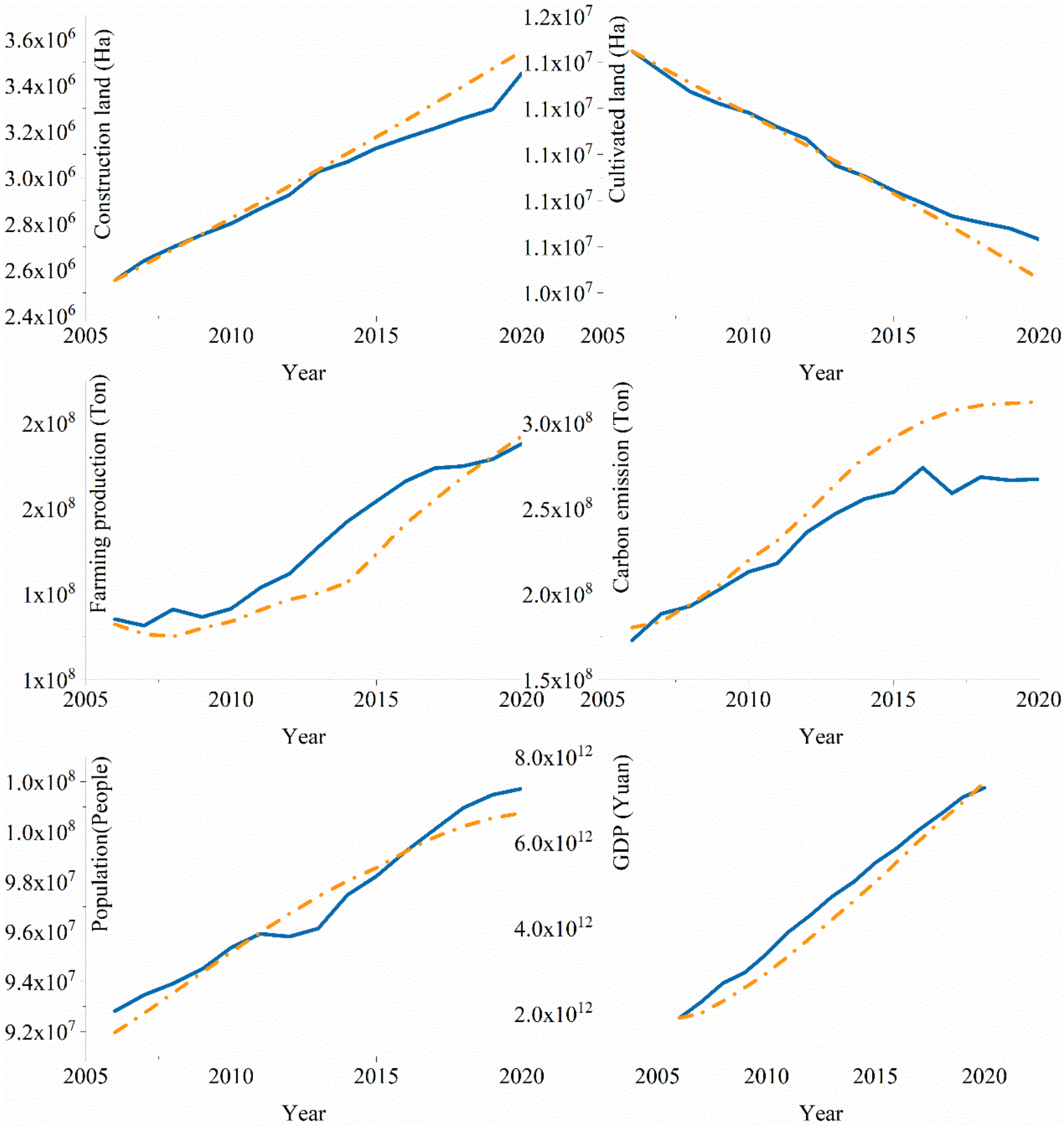


Figure 4.3-3 A comparison of the observed and simulated behaviors of construction land, farmland for cultivation, agricultural production, carbon emissions, population, and GDP. Blue solid lines represent historical data, and yellow dashed lines represent simulated data.

4.3.4 Sensitivity analysis

To enhance the credibility and applicability of the model, a two-step sensitivity analysis was conducted to examine how uncertainties in input parameters may influence simulation outcomes. This process is essential in SES modeling, where many parameters are derived from empirical estimates or expert judgment and thus carry inherent uncertainty (Cooper, 2018; Kotir et al., 2016).

The first stage (Figure 6.3-11) involved a local sensitivity test in which selected parameters and graphical variables were independently varied by 10% above and below their baseline values. By adjusting one variable at a time and holding all others constant, this method enables a straightforward assessment of how individual factors shape system behavior. The model's responses were interpreted using widely accepted criteria for system dynamics models, focusing on the magnitude, direction, and consistency of change (Maani & Cavana, 2007; Pham et al., 2021).

The second stage adopted a global sensitivity approach using Monte Carlo simulations, which allow for the simultaneous perturbation of multiple uncertain parameters (Figure 6.3-12). This method is well-suited to evaluating systemic risks and identifying the parameters most responsible for variability in model outputs (Rachmawati & Kim, 2023). In this analysis, each selected parameter was assigned a uniform probability distribution within ±20% of its initial value. This distribution was chosen to reflect the absence of prior knowledge about the likelihood of different parameter values, ensuring that all values within the range were equally probable (Jeon & Shin, 2014; Tian, 2006). A total of 500 simulations were run, with the model randomly sampling from the defined distributions to generate a spread of plausible outcomes across the parameter space (Zhang & Li, 2023).

Due to limitations in the sensitivity testing module of the modeling platform, only exogenous constants – such as demographic rates and physical coefficients – were included in the Monte Carlo process. Time-dependent graphical functions could not be randomized directly. Nonetheless, the results provide valuable insight into the stability and responsiveness of the model under uncertainty, offering guidance for future scenario exploration and policy applications.

4.3.5 Scenario analysis

To explore potential trajectories of land use and ecosystem service interactions over the simulation horizon of 2020 to 2100, a scenario-based analysis was conducted under varying assumptions. This analysis aimed to explore the system's behavior under a range of plausible future conditions shaped by environmental change and socio-economic transformation. Scenario analysis serves as a strategic tool for anticipating system responses beyond linear trends and for supporting long-term policy planning under uncertainty.

The scenario framework was informed by the results of the sensitivity analysis, as well as by relevant long-term development targets and climate mitigation goals outlined in national strategies and international assessments. In particular, references were drawn from China’s low-carbon development plans (2021 – 2100), China’s Updated Nationally Determined Contributions (2021), and the broader global narratives provided by the IPCC Sixth Assessment Report (2023). A total of 54 exploratory scenarios were developed and tested to capture the diversity of possible system pathways. The analysis proceeded in three stages:

(i) BAU scenario was simulated to represent the system's baseline trajectory in the absence of additional interventions.

The BAU scenario is a common benchmark in system dynamics modeling, as it provides a reference point against which the effects of alternative assumptions can be compared (Sterman, 2000).

(ii) A set of alternative scenarios was generated by adjusting key variables and structural assumptions, both individually and in combination (Maani & Cavana, 2007), including changes in different climate conditions, afforestation and carbon emission policies, water-saving measures under climate change, and adjustments in LULC conversion efficiencies among urban, farmland, grassland, and barren land.

These factors were selected because they represent the most critical drivers of land use–ecosystem service dynamics identified in both the sensitivity analysis and policy documents: climate variables directly influence ecosystem productivity and water balance; afforestation and carbon policies reflect national commitments to carbon neutrality and ecological restoration; water-saving measures capture adaptation needs under climate stress; and LULC conversion efficiencies determine the structural pathways of urban expansion, farmland protection, and ecological land transitions.

(iii) These scenarios were categorized and interpreted using the Shared Socioeconomic Pathways (SSPs) framework (O'Neill et al., 2014).

The SSPs are a set of five globally recognized scenarios developed by the IPCC that describe alternative socioeconomic development pathways and their implications for climate change. Specifically, SSP1 (Sustainability) depicts a pathway of inclusive development and strong environmental stewardship; SSP2 (Middle of the Road) assumes a continuation of historical trends with moderate progress; SSP3 (Regional Rivalry) represents a fragmented world with weak global cooperation and high resource intensity; SSP4 (Inequality) describes a future of deepening disparities between regions and social groups; and SSP5 (Fossil-fueled Development) envisions rapid economic growth strongly dependent on fossil fuels. SSPs were selected because they provide an internationally comparable framework that integrates socioeconomic drivers with environmental pressures, enabling our results to be interpreted not only in a national but also a global context. In particular, the SSP framework helps to situate the Shandong case within broader trajectories of sustainability (SSP1), regional rivalry (SSP3), or fossil-fueled growth (SSP5), thereby linking local ES-LULC dynamics to global policy debates.

The simulated trajectories were assessed in relation to the BAU reference to understand how alternative assumptions might shift the dynamics of the ES-LULC relationship. Instead of focusing on precise numerical predictions, the analysis prioritized the identification of long-term patterns and systemic responses to different policy and environmental conditions. Supplementary Table 6.3-4 provides an overview of the scenario settings and their alignment with the SSP classification.

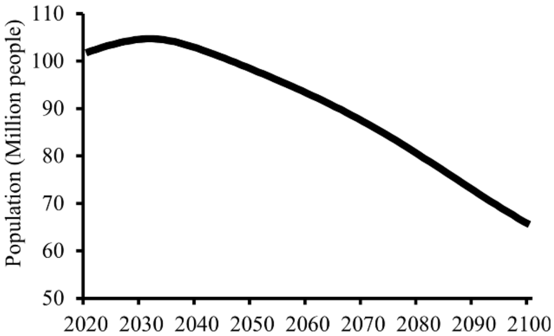
4.4 Results

The LULCESN-SES model generated outputs for key system variables linked to the ES-LULC nexus over the 2020 – 2100 simulation period. These outputs reflect model behavior under business as usual (BAU) case, a range of different "what if" scenarios, and five Shared Socioeconomic Pathways (SSPs).

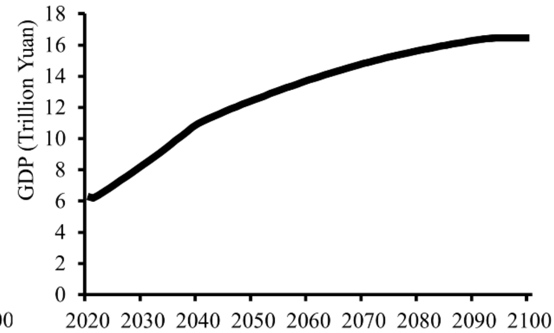
4.4.1 Business as usual (BAU) scenario

Social-ecological scenarios

Population

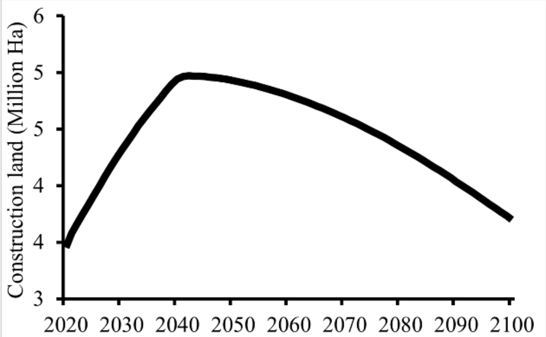


GDP

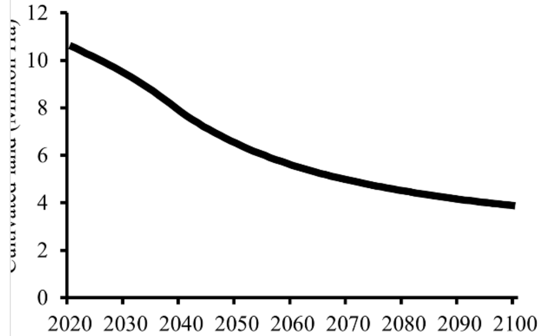


Land use/land cover scenarios

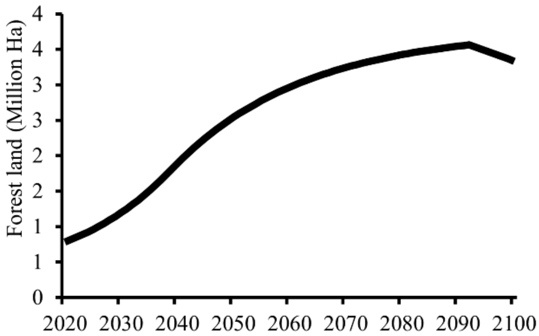
Construction land



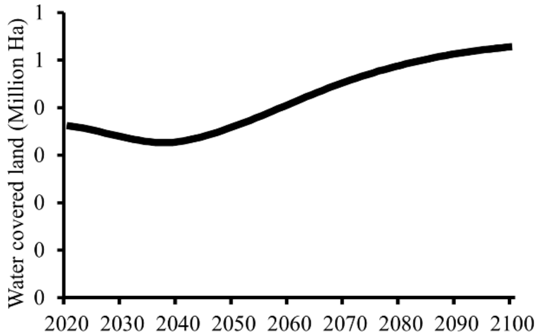
Cultivated land



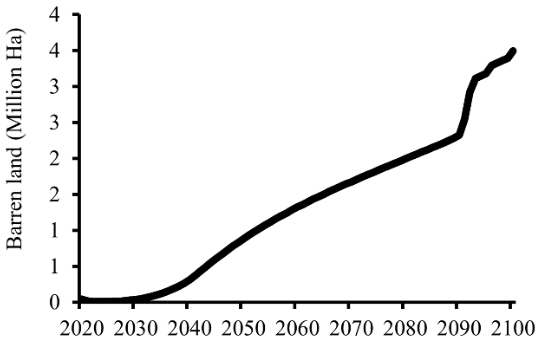
Forestland



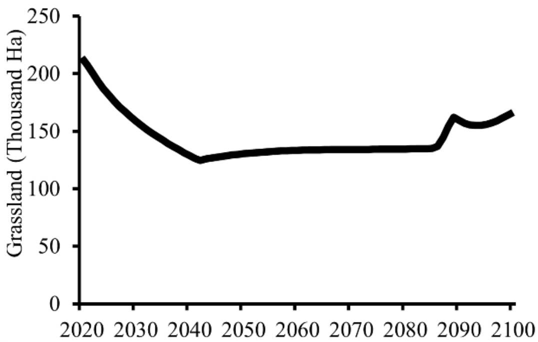
Water covered land



Barren land



Grassland



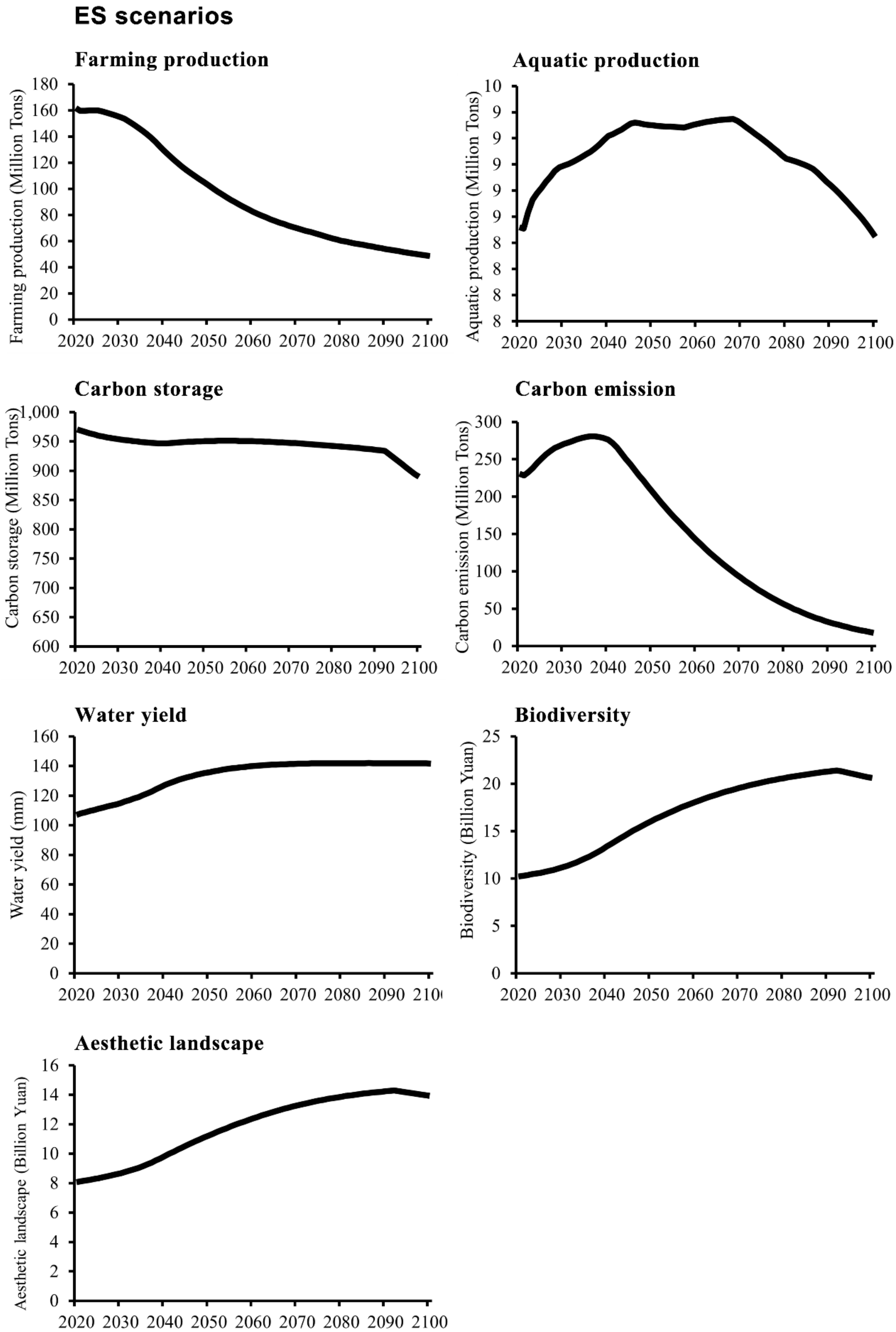


Figure 4.4-1 Key system variables under the BAU scenario over the 2020－2100 period, including population, GDP, LULC categories and selected ESs.

Figure 4.4-1 summarizes the projected trajectories of key system variables under the BAU scenario over the 2020 – 2100 period, including population, GDP, LULC categories and selected ESs. While the economy continues to grow, the population begins to decline after 2030. Yet, construction land demand remains high for a time, showing a delayed adjustment to demographic change. Early land expansion caused a substantial and irreversible reduction in farmland, leading to a marked decline in farming production. This inertia may be related to path dependency in LULC conversion and infrastructure investments. Carbon emissions follow a similar rise and fall trend, aligning with the timing of mitigation policies. Meanwhile, forest recovery drives a gradual increase in water-covered land. However, aquatic production does not rise in parallel, likely constrained by persistent temperature increases. Ecological restoration efforts – such as reforestation, wetland rehabilitation, and grassland recovery – support a slow but steady improvement in biodiversity and landscape aesthetics over the long term.

4.4.2 Behavior of the ES-LULC nexus under different "what if" scenarios

Table 6.3-4 provides extended narratives contextualized of different " what if " scenarios, and the result shows in Figure 4.4-2 and Figure 4.4-3. Specifically, scenarios 1–10 examined the effects of population and CPI changes on land use and ecosystem service dynamics, with Scenarios 9 and 10 capturing their combined impacts. In Stagnant Growth under Aging Pressure (Scenario 9), a declining population (− 20%) and moderate inflation (+ 30%) will reduce demand for developed land, resulting in a 13% contraction in construction areas and a 9% loss of farmland, with agricultural output falling by 8% compared to BAU in 2100. These LULC contractions will be accompanied by modest ecological gains: forest and water covered land will expand (by 6% and 4%, respectively), aquatic production will rise by 5%, and carbon emissions will drop by 21%, along with slight increases in biodiversity and aesthetic value. Demographic Expansion with Deflation (Scenario 10) will reverse this pattern. A growing population (+ 20%) and declining prices (− 30%) will drive a 15% expansion in both construction and farmland, raising agricultural output and carbon emissions by 15% and 39%, respectively. However, this socio-economic growth will come at an ecological cost: forest and water covered land will decline (− 10%, − 16%), aquatic production will fall by 7%, and biodiversity and aesthetic values will drop by 11% and 9%.

Scenarios 11 to 23 assessed the projected impacts of climate change throughout the simulation period. Specifically, Scenarios 11 to 14 explored increases in mean temperature ranging from 1.5°C to 5.7°C, with the BAU2100 scenario projecting a rise of 3.24°C. When the temperature increases remain within 1.5°C to 2.5°C, most indicators will either remain stable or show slight improvement. In contrast, under the high warming scenario of 5.7°C (Scenario 14), farming production will decline by 39% and farmland will decrease by 26% after 2070. Forest degradation will begin after 2060, resulting in a 42% reduction in forest land and a subsequent 25% loss in carbon storage. Although inland water covered land will expand by 23%, farming production will fall by 21% due to elevated thermal stress. Biodiversity and landscape aesthetics will also be negatively affected, with reductions of 20% and 7%, respectively. Scenarios 15 to 19 examined how changes in precipitation, ranging from a reduction to 348 mm to an increase up to 1,044 mm (relative to the BAU 2100 level of 624 mm), influence system dynamics. Under reduced rainfall (Scenarios 15 to 17), all key system variables will exhibit declining trends, whereas increased precipitation (Scenarios 18 and 19) generally will lead to improvements across most indicators. Interestingly, although reduced rainfall (from 624 mm to 348 mm) clearly will resulte in marked reductions in natural land cover and related ESs, excessive rainfall (from 624 mm to 1,044 mm) also will trigger land degradation and a consequent loss of ecosystem functions when compare to the BAU scenario projected for around 2100. Scenarios 20 to 23 further evaluated the combined effects of temperature and precipitation changes. Under scenarios with moderate warming and increased precipitation (Scenarios 20 and 21), natural land, ESs, and GDP all exhibit improvements. However, excessive rainfall results in losses of both agricultural and forest land (-27%), alongside declines in agricultural production (− 24%) and carbon storage (− 20%). In the high-temperature and drought scenario (Scenario 23), all key system variables show declining trends. The most severe impacts are observed in ESs associated with natural land systems. These included substantial reductions in forest land (− 47%), water covered land (− 100%), and cropland (− 25%), along with marked declines in carbon storage (− 26%), water yield (− 79%), aquatic production

(− 87%), and agricultural production (− 47%). Other critical variables, such as biodiversity, landscape aesthetics (both − 56%), and GDP (− 36%) will also negatively affected. Scenario 22, representing moderately arid and warm conditions, will cause damage to forest land (− 30%) and cropland (− 27%) that will be comparable to the effects of Scenario 21, characterized by mild but excessive rainfall.

Scenarios 24 to 29 evaluated the impacts of water consumption patterns under climate change throughout the simulation period. In Scenarios 24 and 25, changes in water consumption (+30% / − 30%) directly influenced water area (+37% / − 37%), which in turn affected key water-related variables, including aquatic production (+12% / − 13%), agricultural production (+5% / − 5%), and landscape aesthetics (+ 14% / − 14%). Water management strategies under extreme climate conditions further amplified the ecological impacts of climate change. The simulation outcomes were consistent with the trends observed in previous climate change scenarios (Scenarios 20 and 23). Notably, under extreme heat and drought conditions (Scenarios 26 and 27), the water-saving scenario was able to delay the complete loss of water area by 30 years compared to the high-consumption scenario, thereby providing a critical window for exploring sustainability strategies under extreme conditions.

Scenarios 30-32 reveal the effects of changes in urbanization rates. When the urbanization rate exceeds the BAU threshold of 80% and reaches 92% (Scenario 30), construction land expands (by 10%), accompanied by increases in forest land (+ 20%) and water covered land (+ 39%). While this transition enhances landscape aesthetics (+ 24%), biodiversity (+ 20%), aquaculture yield (+ 13%), and aquatic production(+ 13%), it results in significant losses in farmland (− 47%) and agricultural output (− 51%), along with a sharp rise in carbon emissions (+ 35%). Conversely, constraining the urbanization rate to 60% reverses these patterns (Scenario 31), favoring farmland preservation (+ 86%) and production(+ 83%), while reducing urban-related land uses (constructed land: − 15%, forestland: − 37%, water body: − 91%) and ecosystem aesthetics (− 51%), as well as lowering overall carbon emissions(− 39%).

Farmland management plays a critical role in safeguarding food security. An increase in per capita farmland management area (Scenarios 33 and 34) substantially mitigates farmland loss (+68% and +112%) and doubles food production. However, this expansion encroaches upon water covered land (− 59% and − 100%), resulting in nearly 50% loss in fisheries yield. Carbon storage initially declines before stabilizing, while biodiversity and landscape aesthetics remain stagnant at the 2020 level. In contrast, Scenario 35, characterized by a reduction in farmland management per capita, farming production outcomes similar to the BAU trajectory, indicating that without sustained and effective management efforts, farmland systems are unlikely to achieve dual gains in productivity and ecosystem functions, and may instead remain in a degraded state.

The rate of grassland degradation (Scenarios 36 ‑ 38) has limited effects on LULC patterns and ESs, likely due to the small share of grassland in the region. Similarly, carbon emission policies of varying intensities (Scenarios 39 ‑ 42) show no substantial changes, possibly because regional models do not account for global climate feedbacks. However, Scenario 40 slightly improves afforestation efficiency (+5%) while reducing water covered land (− 3%), indicating potential trade-offs among ecosystem functions.

Afforestation and the expansion of fast-growing plantations (Scenarios 43 ‑ 45) substantially reshape LULC patterns and ESs. Under the extreme afforestation scenario (Scenario 44), large-scale cropland conversion is completed by 2050 (− 30%), and by 2100, nearly half of water covered lands are replaced by forests, threatening food (− 18%) and fisheries supply (− 21%). In contrast, carbon storage (+30%), biodiversity (+32%), and landscape aesthetics (+8%) increase alongside forest expansion. However, under weak forest protection, the impacts are largely comparable to the BAU scenario.

Unused land has limited effects on key system variables, contributing marginally to construction land expansion before saturation (Scenarios 46 ‑ 48). When conversion slows (Scenarios 46 and 47), water covered land and aquatic production increase by 7% and 4%, respectively (Scenario 46). Faster conversion (Scenario 48) leads to a 5% increase in forest land, while other variables remain largely unchanged.

Integrated scenario analysis reveals that LULC pathways play a decisive role in shaping the trade-offs and synergies among ESs. The sustainable scenario (Scenario

49) limits construction land expansion (− 7%) and maintains cropland and forest lands near 2020 levels (+150% and − 78%), thereby stabilizing food production (+144%) and carbon storage while reducing carbon emissions generally. Slight declines are observed in biodiversity and landscape aesthetics (minor decrease), along with slower economic growth (− 35%). In contrast, the unmanaged scenario (Scenario 50) leads to substantial losses in cropland (− 45%) and food production (− 48%), with a significant increase in water covered land (+50%) but only limited improvement in fisheries yield due to climate constraints. Carbon storage declines (− 12%), and emission reductions are delayed until after 2050. Although economic output increases (+18%), ecosystem stability is significantly compromised. Overall, LULC strategies profoundly affect the configuration of ESs, underscoring the need for integrated and adaptive management within resource and planetary boundaries to balance ecological and economic goals.

4.4.3 Behavior of ES-LULC nexus under different shared socio-economic pathways (SSPs)

This study also assessed a set of hypothetical scenarios aligned with the five Shared Socioeconomic Pathways (SSPs). Table 6.3-4 provides extended narratives contextualized to this study. As shown in Figure 4.4-2 and Figure 4.4-3, LULC & ES under SSP1 (Sustainability) and SSP2 (Middle of the Road) follow a trajectory similar to that of the BAU scenario. In contrast, SSP3 (Regional Rivalry), SSP4 (Inequality), and SSP5 (Fossil-fueled Development) are associated with more pronounced LULC changes and greater losses in ESs, underscoring the systemic risks driven by fragmented governance, widening social disparities, and fossil-intensive growth strategies.

Farmland area remains relatively stable only under SSP1 and SSP3 (+156% and +160%, respectively), while all other pathways show varying degrees of decline, with SSP2 exhibiting the most rapid reduction (− 27%). Construction land closely correlates with population dynamics, generally following a similar trajectory. Except for SSP5, which shows sustained growth before levelling off (+74%), all other scenarios experience a modest initial increase followed by a decline. Under SSP1, SSP3, and SSP4, construction land remains below BAU levels throughout the simulation. Forest land remains the lowest under SSP3 (-83%), while most other scenarios show an initial increase followed by a slight decline. The highest forest coverage is found in SSP2, closely aligning with BAU, followed by SSP4 (− 42%). Among all land categories, water covered land exhibits the most pronounced differences across SSPs. Under SSP1 and SSP2, the water area increases progressively over time. In contrast, water covered land vanishes entirely in SSP5, SSP4, and SSP3, disappearing by 2040, 2048, and 2055, respectively.

Provisioning services, represented by food production and aquatic yield, declined to varying degrees across all SSPs. For food production, SSP1 and SSP3 experienced the least reduction, reaching +140% and +126% relative to the baseline. In terms of aquatic yield, SSP1 and SSP2 showed the slowest declines (− 24% and − 4%, respectively). SSP5 recorded the lowest provisioning services overall, with a 14% drop in food production and a drastic 79% decline in aquatic yield. Regulating services – represented by carbon emissions, carbon storage, aquatic production, and biodiversity – exhibited distinct responses across SSPs. Carbon emissions increased sharply under SSP5, peaking around 2050 before leveling off at +4346%. In contrast, all other pathways showed varying degrees of reduction, with SSP1 achieving the lowest emission levels (− 60%). Carbon storage declined steadily in SSP5, with a marked drop after 2070 (− 27%). Other scenarios remained largely stable or showed slight decreases. Notably, SSP4 experienced a minor cliff-like drop around 2080, accelerating the decline (− 8%). Aquatic production followed three distinct patterns: slight increases under SSP1 and SSP2 (similar to BAU), stabilization under SSP4 (− 31%), and sharp declines under SSP3 and SSP5 (− 83% and − 93%, respectively), approaching near-zero levels. Biodiversity trends largely mirrored those of landscape aesthetics, a cultural service indicator. SSP2 saw continuous improvement (similar to BAU), SSP1 and SSP4 remained relatively stable (around − 52%), while SSP3 and SSP5 declined moderately until 2044 before flattening out (approximately − 74%).

Under SSP5, the population continues to grow until 2050 and then stabilizes, ultimately reaching a level 79% higher than BAU by 2100. In contrast, all other scenarios experience population decline after 2035, albeit at varying rates. GDP outcomes also vary across scenarios. SSP2 yields the most favorable economic performance, closely aligning with the BAU trajectory. In comparison, SSP1 and

SSP5 result in the lowest GDP gains, both approximately 50% below BAU levels by the end of the simulation.

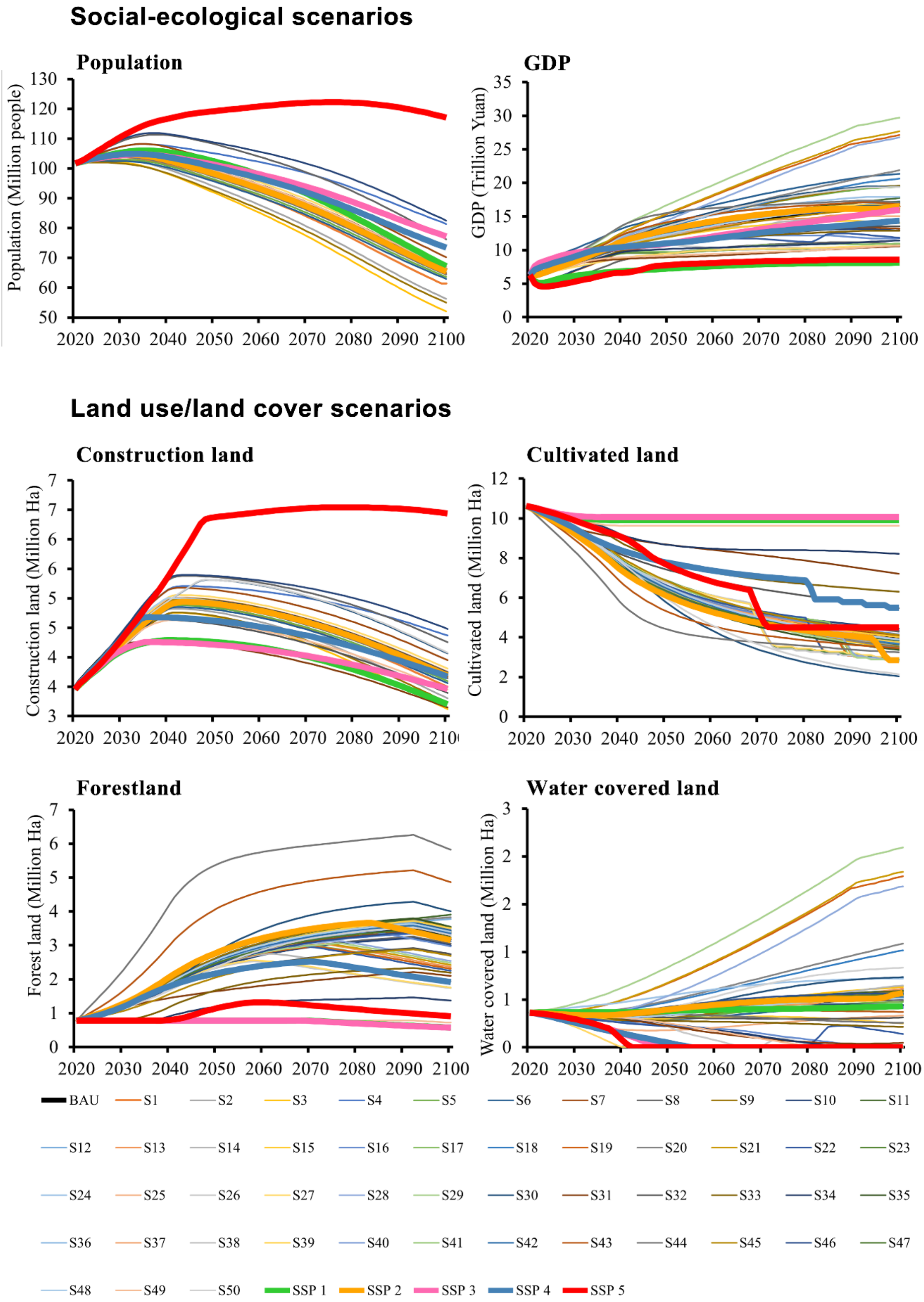


Figure 4.4-2 Social-economic and LULC simulation of ES-LULC nexus over the simulation period (2020 – 2100) under different "what if" scenarios and SSPs.

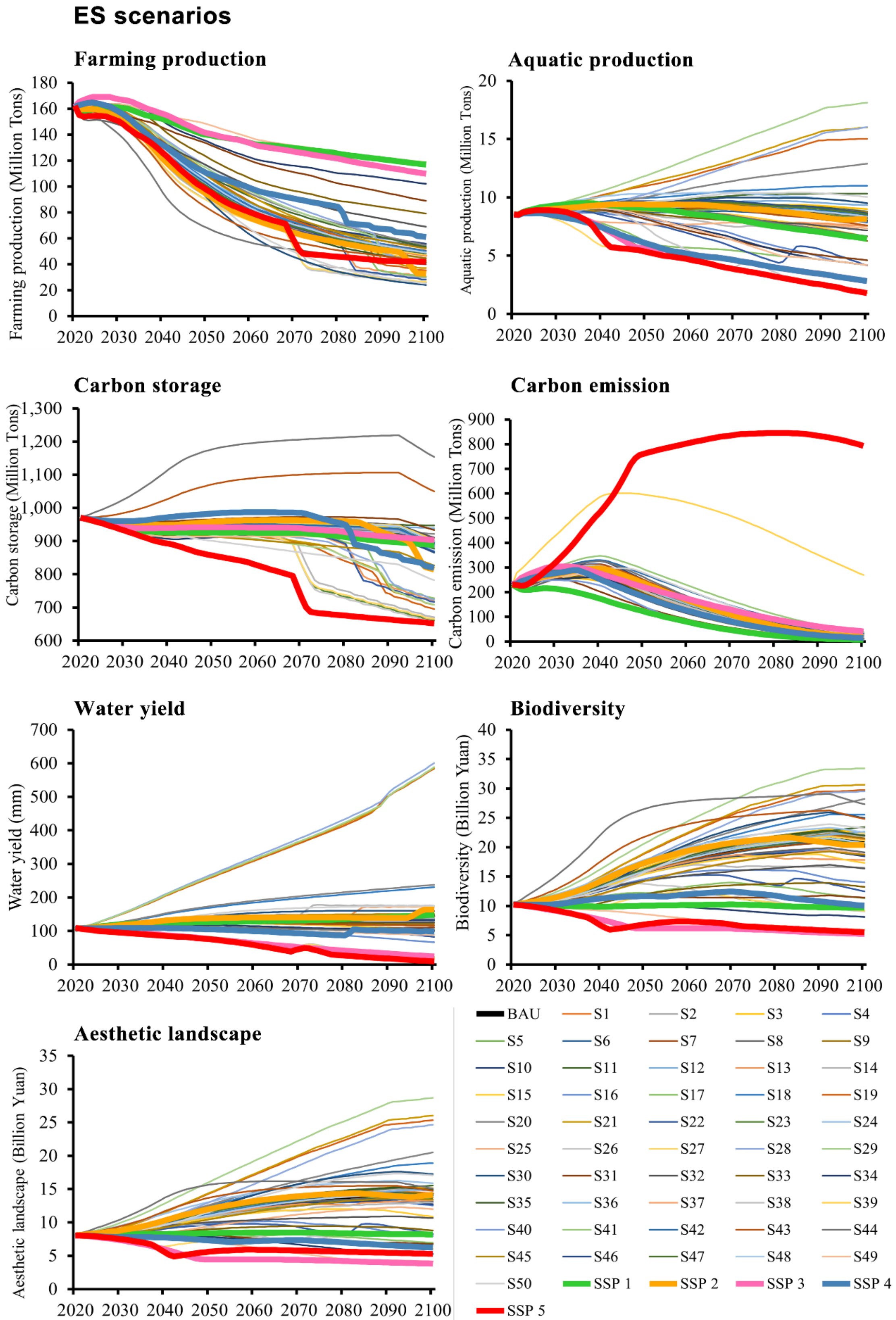


Figure 4.4-3 Ecosystem services simulation of ES-LULC nexus over the simulation period (2020 – 2100) under different “what if” scenarios and SSPs.

4.5 Discussion

This study employed the SES perspective to assess the long-term co-evolution of LULC and ESs in Shandong Province under varying socio-economic and climate conditions. Under the BAU scenario, the model reveals growing tensions between land system dynamics and the ecological capacity to support essential ESs. Although the total population is projected to decline around 2030, the urbanization rate is projected to reach 80% by 2040, driving continued growth in the urban population. Urban land growth remains tightly coupled with demographic restructuring, reversing after the urban population peaks. This trend is consistent with prior findings that identify population thresholds as key constraints on urban land expansion in Shandong (Wang et al., 2023). In contrast, cultivated land declines steadily under the combined effects of urbanization and climate change, shrinking by nearly 70% by 2100 and accompanied by a 60% drop in agricultural output – posing severe risks to regional food security. This projection is consistent with a recent study showing that even under a 1.5°C global warming scenario, China could lose up to 35% of its arable land (Lv et al., 2025); under the BAU trajectory modelled here, the projected 3.24°C increase implies even greater degradation risk. Although forest, shrubland, and water-covered areas expand under restoration policies, such gains remain marginal relative to extensive cropland loss, resulting in limited improvements in regulating and cultural services. Notably, despite steep reductions in carbon emissions after 2040 under carbon neutrality efforts, carbon stocks continue to decline slightly, indicating that early-stage land degradation has already compromised long-term sequestration capacity (Lal et al., 2018; Zheng & Zheng, 2023b). Meanwhile, persistent warming and reduced precipitation further constrain ecological recovery, limiting the restoration potential of key regulating functions (Guo et al., 2024a).

Compared to the BAU scenario, the results indicate that ESs in Shandong are exposed to compound risks driven by interacting climatic, hydrological, and socioeconomic forces. Given its chronic water scarcity, Shandong's ES-LULC system shows higher sensitivity to precipitation variability than to temperature rise, positioning water availability as a critical determinant of system stability (Fu et al., 2019; Liu et al., 2024). Persistent warming (1.5 – 5.7°C), declining rainfall (− 50% to − 80%), and intensified water use jointly contribute to sharp declines across most ES and LULC indicators. Under extreme hot-dry conditions, cropland and forest area shrink significantly, water bodies vanish before 2050, and both provisioning and regulating services collapse. This shift reflects the breakdown of internal feedbacks and the severing of ecological linkages across services, signalling a transition into an irreversible degradation trajectory (Steffen et al., 2018). Notably, excessive precipitation does not necessarily improve system performance; in such scenarios, agricultural land loss and service decline still occur, suggesting nonlinear and threshold-based responses to hydrological input that destabilize land-service coordination. In contrast, under the same extreme climate conditions, water-saving strategies can delay the total loss of water bodies by approximately 30 years, offering a limited but critical window to sustain core ecological functions. Previous studies have similarly emphasized that managing the growth of agricultural and industrial water use and optimizing water allocation structures can alleviate water scarcity in Shandong and enhance overall system resilience (Zhang et al., 2022). These findings highlight the need for resilience strategies that move beyond temperature mitigation and focus on integrated water governance and strengthened cross-service feedback.

Socioeconomic variables and LULC trajectories significantly shape the structural coordination and resilience of ES-LULC systems by reconfiguring development intensity and spatial patterns. Simulation results indicate that population growth coupled with declining CPI (Scenario 10) may enhance short-term provisioning capacity and economic indicators, but also intensify the encroachment on natural land systems such as forests and water bodies, leading to sustained degradation of regulating and cultural services, including carbon storage, biodiversity, and landscape aesthetics. This finding is also supported by Marques et al. (2019). In contrast, population deceleration and reduced consumption (Scenario 9) help ease development pressure, facilitate natural system recovery, and strengthen regulating functions. When urbanization exceeds critical thresholds or farmland management intensifies (Scenarios 30, 33 – 34), farming production may improve, but this is accompanied by waterbody shrinkage, increased carbon emissions, and declining aquatic production services, revealing weakened feedback coordination between provisioning and regulating functions (Guo et al., 2024b). Under high-intensity afforestation pathways (e.g., Scenario 44), regulating services such as carbon sequestration and biodiversity improve substantially, but are offset by the ongoing loss of cropland and water bodies, resulting in sharp declines in food and aquatic production. Similar effects have been noted by Fang et al. (2022b), who found that large-scale afforestation can reduce water availability and contribute to the disappearance of aquatic ecosystems. Overall, service coordination is highly sensitive to socioeconomic dynamics and LULC interventions. Development pathways driven by single-objective priorities tend to destabilize internal feedback mechanisms and erode system adaptability. Future governance should be grounded in an integrated understanding of demographic change, economic incentives, and spatial configuration to rebuild ecosystem service coordination and long-term resilience.

Under the Shared Socioeconomic Pathways (SSPs), different development logics lead to clearly differentiated trajectories in ESs and system resilience. SSP1, the sustainability pathway, maintains strong service coupling through ecological conservation and cross-sectoral governance, enabling positive outcomes such as water and farmland restoration and carbon reduction, thereby demonstrating the highest system resilience. SSP2 largely follows the BAU trend, with moderate ES fluctuations and limited improvements in regulating functions or overall system structure. SSP3, constrained by regional rivalry and fragmented governance, suffers from chronic underinvestment in regulation; although farmland area remains high, water bodies, biodiversity, and cultural ESs continue to decline, resulting in accumulating system vulnerability. SSP4 exhibits localized structural gains – particularly in forest cover – but widening social inequality and weak institutional coordination lead to uneven access to regulating services, limited cultural recovery, and weak system coherence. SSP5 reflects a rapidly degrading, resource-intensive trajectory characterized by soaring emissions, regulatory collapse, and destabilized provisioning systems, pushing the system toward irreversible thresholds, as also shown in the findings of Guo et al. (2024b). Collectively, these scenarios illustrate that development pathways not only influence ES levels but also shape functional integrity and tipping risks, underscoring the need for recovery strategies grounded in structural pathway recognition and process-based understanding (IPBES, 2019a).

4.6 Policy Implications

This study highlights a dual challenge in regional development: managing land abandonment driven by population decline, urban contraction, and natural land degradation, while also fostering greater synergy between ES and economic growth. To address this, there is an urgent need for integrated LULC and ecological restoration policies that can guide the sustainable transformation of socio-ecological systems.

All scenarios show same trend of population decline and urban contraction, especially S1 to S3, which reduced expansion of construction land slows farmland loss. Rising food prices temporarily stabilize primary sector GDP. However, this passive stability conceals deeper risks, including declining productivity, labor shortages, irrigation water scarcity, and farmland abandonment (Hou et al., 2021; Xu et al., 2019b). Policymakers should address this structural lag by enhancing farmland use through land revitalization, use-based incentives, agricultural insurance subsidies, and coordinated food and water pricing mechanisms (Pan et al., 2022; Si et al., 2023), to secure regional food supply and contribute to the SDG 2 goal of zero hunger through sustainable agriculture. In China, and particularly in provinces such as Shandong facing rural depopulation and underutilized farmland, this strategy is essential for maintaining baseline food production capacity. Empirical evidence confirms that targeted subsidies and pricing policies can effectively stabilize land productivity (Pan et al., 2022).

Declining urban population and reduced demand for construction land have released spatial resources, offering opportunities for ecological restoration and industrial transition (S1 – S3, S31 – S32, S49). Forest recovery and landscape enhancement have stimulated growth in the tertiary sector, reflecting a shift in land function from construction to ecological and service-oriented uses (Puppim et al., 2022). To harness this potential, policies should repurpose underused urban land into green-blue infrastructure or multifunctional service spaces, supported by tax incentives, transferable land quotas, and service-oriented development mechanisms. In the near term, ecological zoning and multifunctional LULC mechanisms should be incorporated into urban renewal pilots to enhance implementation readiness, while aligning with SDG 11 (Sustainable Cities) and SDG 15 (Life on Land). This global perspective also resonates with China's National Territorial Spatial Planning Outline (2021 – 2035), which emphasizes revitalizing underutilized land and improving spatial efficiency (Central Committee of the CPC & State Council, 2021).

Under climate change and ongoing structural transition, drought and water scarcity has become a critical constraint on food system stability, ecosystem service provision, and urban–rural water supply reliability in Shandong (in S11 – 29) (Zhang et al., 2022). A coordinated water security framework is needed to balance agricultural, ecological, and domestic water demands. Key measures include expanding water-saving irrigation, utilizing non-conventional water sources, enhancing supply buffering systems (Owens et al., 2022; Ristvey et al., 2019), and establishing ecological water allocation priority to safeguard river baseflows, wetland water levels, and aquatic habitats (Li et al., 2021). Water governance should be embedded in an integrated land–water–climate framework to enhance synergies among food security, ecosystem services, and public health (Ramos et al., 2022). This strategy supports the dual objectives of SDG 6 – improved agricultural efficiency and ecological restoration – and aligns with the SSP1 sustainability pathway, which emphasizes resilient regional water systems and ecological integrity.

Model results indicate that most system indicators remain stable or improve under 1.5 – 2.5°C warming, but risks rise sharply beyond 2.5 – 3°C (IPCC et al., 2021). Without intervention, continued development along SSP3 – 5 pathways may significantly undermine the region’s ability to achieve SDG 2, 6, and 13 (Roy et al., 2024). A proactive temperature control approach is thus essential to meet the Paris Agreement target of keeping global warming below 2°C (United Nations, 2015). Regionally, this research recommends establishing dual carbon controls (total and intensity), advancing energy system decarbonization, low-carbon land use, and ecological carbon sink enhancement (Song et al., 2023; Zheng et al., 2019). These measures should be integrated into a ES-LULC socio-economic governance framework to strengthen long-term climate resilience and deliver cross-sectoral mitigation benefits.

4.7 Conclusion

This study finds that the combined effects of biophysical stressors – namely rising temperatures and declining precipitation – and socio-economic transitions such as population decline and rapid urbanization are accelerating the degradation of natural land cover, with cascading impacts on ESs. Under the most extreme climate scenario (a 5.7°C increase in temperature and 50% reduction in rainfall), all key ES indicators decline simultaneously, natural land loss multiplies, and the system's resilience deteriorates sharply. The complete disappearance of surface water by 2050 emerges as a clear warning of an impending ecological tipping point. Yet, the results also suggest that adopting water-saving LULC practices could delay this collapse by up to 30 years, offering a window for adaptive intervention.

Simulations across SSPs show that divergent development trajectories have profound implications for ecosystem dynamics. Regional fragmentation under SSP3, rising inequality in SSP4, and fossil-fuel-driven growth in SSP5 all contribute to varying degrees of ecological degradation, particularly the erosion of regulating services such as carbon storage and water retention.

Ensuring the long-term stability of ecological functions will require integrated, cross-sectoral action. This includes maintaining the integrity of farmland, preventing land abandonment and degradation, and reinforcing agricultural resilience through targeted subsidies and technical support. Urban planning should prioritize the ecological repurposing of underutilized land, including wetland restoration, green corridors, and urban carbon sinks. Equally, water governance must prioritize ecological baseflows to minimize unsustainable competition between agricultural and urban users. Most importantly, the global temperature increase must be kept well below 2°C in accordance with the Paris Agreement to prevent irreversible disruptions to regional ecosystems (United Nations, 2015). Achieving this requires a comprehensive carbon governance framework that targets both total emissions and emission intensity, enabling coordinated management of land, water, and carbon systems.

As with any system dynamics approach, the model presented here is shaped by structural and parametric assumptions that introduce some degree of uncertainty. The findings and recommendations should therefore be interpreted within the context of these scenario-based constraints. While the model is applied to Shandong Province, its core feedback structure and dynamic interactions are transferable. This framework could be adapted to other regions experiencing similar resource and climate pressures, such as South Asia or East Africa. Future work could expand the model's scope by incorporating more diverse LULC systems (e.g., livestock or cryosphere components), accounting for intra-annual variability, integrating a broader range of climate variables (e.g., wind, evapotranspiration), and simulating compound events such as alternating droughts and floods. These enhancements would strengthen the model's capacity to support socio-ecological adaptation under accelerating global change.

Chapter 5 Synthesis and conclusion

5.1 Knowledge contributions and synthesis across the three papers

The first paper conducts a systematic review of 146 peer-reviewed studies on ES and LULC interactions in China's mountainous regions, retrieved from Chinese (CNKI) and English (Scopus, Web of Science) databases and published between 2007 and 2022. The analysis reveals significant differences in spatial scale, methodological approaches, and temporal coverage. English-language studies emphasize regional-scale assessments and process-based modelling, whereas Chinese-language studies primarily adopt local-scale static valuation tables and ES mapping methods. These divergent approaches contribute to fragmented evidence and hinder the policy relevance of cross-scalar comparisons. Furthermore, nearly 78% of the studies adopt a retrospective perspective, rarely considering systemic feedbacks or scenario-based projections. The review identifies three critical gaps that shape the research agenda: insufficient use of dynamic models, weak multi-scale integration, and a lack of scenario-based system analysis. Collectively, these insights provide a conceptual and methodological foundation for the thesis, guiding the empirical and modelling components and framing a coherent agenda for advancing ES-LULC co-evolution research in mountainous socio-ecological systems.

The second paper analyzes long-term time series data (1950 – 2020) from Shandong Province to reveal coupled imbalances among LULC, ESs, and socio-economic drivers. It identifies urban expansion, tourism development, and wetland loss as key anthropogenic pressures driving the decline of regulating services and shaping complex feedbacks within the socio-ecological system. Granger causality tests establish lead–lag relationships among provisioning, regulating, and economic variables, showing that urban growth consistently reduces wetlands, water bodies, and carbon stocks, while tourism enhances provisioning services but intensifies regulatory degradation. EKC modeling shows that most ESs do not exhibit recovery turning points, challenging the prevailing assumption that economic growth inevitably yields ecological restoration. PCA further reveals a marked decline in the connectivity of regulating services as GDP rises, indicating a progressive weakening of systemic feedback integrity. Together, these findings provide a deeper empirical basis for understanding ES-LULC co-evolution and offer critical input for structuring the causal pathways in the system dynamics model developed in the subsequent chapter.

The third paper develops a regionally calibrated SD model to simulate the long-term evolution of ES-LULC in Shandong Province under multiple socio-environmental scenarios. Building on the empirical foundations of the previous chapter, the model incorporates seven LULC categories and seven ES types, integrating key feedback loops, trade-offs, and potential tipping points. Results reveal strong path dependency and non-linear responses of the ES-LULC system to stressors such as warming, drought, and urban expansion. For example, large-scale afforestation enhances carbon storage but triggers water scarcity under reduced precipitation, while controlling urban expansion slows the degradation of regulating services. Under compounded extreme scenarios, services including water yield, aquatic production, and biodiversity exhibit simultaneous declines around 2050, indicating proximity to a coupled system threshold. The model also identifies effective intervention levers – such as water-saving measures, farmland protection, and urban boundary control – that can delay degradation and help keep the system within a safe operating space. This work advances a novel modelling paradigm for detecting system thresholds and feedback-sensitive risk zones, and provides a forward-looking tool to support adaptive ES-LULC governance under uncertainty.

Taken together, the three papers establish a progressive and multi-dimensional research framework that systematically investigates the co-evolution of ES-LULC in mountainous China. From literature synthesis to empirical identification and dynamic modeling, the research uncovers the temporal patterns, feedback structures, and tipping risks within ES-LULC interactions. By integrating quantitative testing (e.g., Granger causality, EKC), structural analysis (e.g., sPCA), and system dynamics modelling, this thesis advances the empirical foundations of complex SES dynamics and offers a coherent toolkit for identifying systemic imbalances, assessing transformation risks, and informing targeted interventions at the regional scale. This integrative approach is particularly applicable to high-risk ecological contexts facing intense resource pressures and socio-environmental change.

5.2 Methodological and conceptual novelty

This research develops an integrated methodological framework to investigate ES-LULC coupling dynamics and adaptive interventions in mountainous regions of China. First, it applies the ROSES protocol to systematically review 146 peer-reviewed articles in both Chinese and English, bridging language barriers and revealing significant thematic gaps in ES-LULC research – particularly the lack of dynamic modelling, scenario-based exploration, and multi-sectoral integration in mountainous contexts. Second, it introduces a novel empirical framework that combines Granger causality tests, EKC modelling, and sPCA to capture the directional influence of socioeconomic processes, nonlinear ecosystem responses, and structural degradation in system connectivity. Third, drawing on these empirical findings, a regionally calibrated SD model is developed to simulate long-term ES-LULC trajectories under integrated climate-land policy scenarios. This SD model incorporates key feedback loops, trade-offs, and potential tipping points, offering a robust tool for threshold identification and scenario-based governance. Collectively, the study bridges the gap between empirical evidence and dynamic modelling, advancing an adaptive, policy-relevant modelling paradigm for high-risk socio-ecological systems under uncertainty.

5.3 Policy implications

This thesis advances an integrated understanding of how ES-LULC co-evolve under the combined pressures of socioeconomic development and climate change, offering empirically grounded and model-informed insights for future governance in Shandong Province. The co-evolutionary analysis and system dynamics modelling collectively demonstrate that the ES–LULC system exhibits strong path dependence, feedback sensitivity and nonlinear responses—characteristics that conventional static assessment tools are ill-equipped to capture. These findings underscore the need to embed dynamic, threshold-aware modelling frameworks into existing planning and regulatory instruments to enable more anticipatory and resilience-oriented land governance.

Shandong has implemented a range of ecological and land-use policies—including the Ecological Redline system, permanent prime farmland protection, the Yellow River Delta wetland conservation programme, Sponge City initiatives, basin-level restoration projects, and the province's 2021–2035 Territorial Spatial Plan—that together provide an important institutional foundation for sustainable land management. The results of this thesis, however, indicate that these instruments remain insufficient for addressing deeper systemic risks, largely because they do not yet incorporate cross-sectoral feedbacks, cumulative pressures, ecological thresholds or long-term scenario foresight. As a consequence, governance outcomes often remain fragmented and reactive.

Empirical findings (Chapter 3) identify urban expansion, wetland degradation and tourism-driven land conversion as the principal forces driving the decline of regulating services. These pressures require a shift from project-based and engineering-oriented restoration towards more structural interventions—such as enforceable urban growth boundaries, legally designated wetland buffer zones, restrictions on ecological encroachment by tourism development and strengthened high-quality cropland protection. The absence of ecological recovery turning points in the EKC analysis, together with the observed decline in regulating-service connectedness with rising GDP, further challenges the assumption that economic growth alone will generate ecological improvement. As such, ecological thresholds and feedback-sensitive constraints need to be formally integrated into land-use, industrial and water-resource policies, promoting development pathways that prioritise system stability.

The system dynamics simulations additionally reveal that water-related services may approach critical thresholds around mid-century under high warming and drought scenarios. At the same time, the model identifies several leverage points—including water-saving policies, watershed and cropland protection, green agricultural practices and urban containment—that can substantially slow ecological deterioration and help maintain the system within its safe operating space. These results highlight a narrow but consequential governance window before 2040 during which integrated land–water reforms could prevent irreversible ecological losses. Given the compound nature of socio-climatic pressures, single-policy interventions are insufficient; instead, coordinated governance frameworks that align spatial planning, ecological compensation mechanisms and water-use regulation are required to achieve systemic coherence.

Institutionalising resilience-oriented governance will require embedding ecological thresholds into territorial spatial planning, river-basin management and environmental impact assessments, thereby providing a regulatory basis for early warning and adaptive policy adjustment. At the national level, aligning Shandong's ES–LULC governance with China's broader Ecological Civilization agenda could transform scenario-based modelling into an actionable policy trigger rather than a purely analytical tool. By transitioning from fragmented, reactive governance to anticipatory, systemic and adaptive approaches, Shandong Province can enhance the long-term stability, resilience and sustainability of its ES–LULC system through the mid-21st century and beyond.

5.4 Limitations and future improvement

Despite the substantial progress made in synthesizing literature, identifying causal mechanisms, and developing dynamic simulations of ES-LULC interactions, this study has several limitations that merit further development.

First, the breadth and contextual depth of the literature integration can be improved. While the review followed the ROSES protocol and synthesized 146 Chinese- and English-language studies – offering a rare focus on ES-LULC dynamics in China's mountainous regions – it remained constrained by database coverage and limited disciplinary crossover. In particular, the review did not systematically capture how institutional evolution and policy contexts shape ES-LULC trajectories. Future work should incorporate multilingual, multi-scalar bibliometric approaches to build a more holistic map of governance, policy and ecological linkages.

Second, the empirical modelling of ES remains limited in ecological representation. Although the Granger-EKC-sPCA framework effectively captured GDP-ES connectivity, several regulating services were measured through indirect proxies, and climate and governance drivers were not fully incorporated. Moreover, ES were primarily inferred from LULC transitions, without integrating key process-based ecological variables (e.g., soil moisture, groundwater, pollution loads). Future research should incorporate remote sensing and sensor-based data, as well as institutional indicators, to enhance both ecological realism and policy relevance.

Third, the SD model's structural flexibility and cross-regional applicability remain limited. While the model successfully integrated policy interventions, climate-LULC scenarios, and feedback loops to identify potential tipping points, it was calibrated for a single region and did not capture cross-regional interactions, market coupling, or global feedbacks. Its scenario design was also based on static assumptions, lacking institutional inertia and adaptive behaviour. Future extensions should incorporate agent-based modelling (ABM) to capture human behaviour and response to changes in ES and LULC, institutional change pathways, and uncertainty propagation mechanisms to better reflect the complexity of SES dynamics.

Fourth, the translation of model outcomes into actionable tools remains underdeveloped. Although the SD model supports scenario simulation and critical threshold identification, it has not yet been operationalized through interactive interfaces or aligned with local planning systems. Future efforts should focus on building user-friendly visualization platforms and early-warning tools to support multi-agency coordination and participatory decision-making.

In sum, this study builds a foundational ES-LULC modelling framework across literature synthesis, empirical diagnosis, and dynamic simulation. Future research should deepen this foundation through cross-scale coupling, process-based ecological integration, behavioural governance modelling, and decision-oriented tool development – facilitating a shift from system diagnosis to policy design.

5.5 Conclusion

This dissertation systematically investigates the co-evolution between LU and ESs in mountainous regions of China, establishing an integrated analytical framework that links literature synthesis, empirical identification, and dynamic simulation. First, the review chapter provides the first focused synthesis of ES-LULC research in Chinese mountains, highlighting spatial, methodological, and scenario-based gaps. It reveals a lack of system-level understanding of SES feedbacks and institutional dynamics, offering contextual and theoretical foundations for subsequent modeling. Second, based on provincial time-series data from Shandong (1950 – 2020), the study develops an empirical framework combining Granger causality, EKC modeling, and sPCA. Results identify urban expansion, tourism-driven conversion, and wetland loss as key drivers of sustained declines in regulating services. ES connectivity declines continuously with GDP growth, without recovery turning points – challenging the classical assumption that economic growth leads to ecological improvement. Third, a regionally calibrated SD model simulates ES-LULC trajectories and potential tipping points under multiple scenarios (2020 – 2100). Under extreme warming and drought, services such as water provision, biodiversity, and water retention show synchronized degradation by mid-century. Yet, targeted interventions – such as water-saving practices, farmland protection, and urban boundary control – can help maintain the system within a safe operating space and delay critical transitions.

Together, these studies establish a closed-loop methodological pathway for ES-LULC research, bridging theoretical framing, empirical evidence, and dynamic simulation. The research offers practical tools and strategic insight into feedback mechanisms, coupling risks, and governance levers in complex SESs. It emphasizes the need to shift from static evaluation to adaptive control, and from fragmented responses to integrated governance—providing scientific foundations and policy guidance for managing land and ESs in high-risk mountain regions under increasing uncertainty.

Chapter 6 Appendix

6.1 Appendix A

Supplementary material: Chapter 2

6.1.1 Systematic review addressed in different categories and description

Table 6.1-1 Systematic review addressed in different categories and description.

HEADERS	Factor	DESCRIPTION
SL. No.		Serial number of paper (Unique ID)
Year		Year of publication (Integer)
Authors		All authors of the paper
Title		Title of the papers reviews
Journal		Name of the journal
Type of research		Category the published manuscript namely, article/book chapters
Keywords		Keywords of the published article - (factor)
Aim/to fill the gap		Main objective of the paper
Spatial scale	**Patch**	$10–10^2$ km^2
	Local	$10^2–10^3$ km^2
	Regional	$10^3–10^5$ km^2
	National	$10^5–10^6$ km^2
Location of the study Area		Location of the research study area

Temporal scale	**Future**	Those that simulate or project land use or ecosystem services beyond the publication date.
	Current	Those using data collected within **three** years prior to publication
	Historical	Those using data collected more than **three** years prior to the publication date of the article.
	Cross-scale	
	Not indicated	

Systematic Focus	**Social**	Studies that primarily focus on human perceptions, behaviors, or social valuation of ecosystem services (e.g., stakeholder surveys, community-based assessment, willingness-to-pay studies).
	Ecological	Studies that emphasize biophysical processes, ecological mechanisms, or natural dynamics of ES and LULC (e.g., InVEST, CASA, soil erosion models).
	Economic	Studies that assess the monetary value of ecosystem services or economic impacts of land use change, using market-based or valuation models.
	Social-ecological	Studies that integrate both social and ecological dimensions, e.g., combining ES supply with stakeholder demand, or spatial mapping with livelihood impacts.
	Ecological-economic	Studies linking ecological data or models with economic valuation, such as biophysical modeling + ESV calculation or cost-benefit analysis of land use decisions.
	Social-economic	Studies that explore human perceptions, behavior, and economic valuation, but do not directly include ecological data or models.
	other	
	Primary data	Data derived from sampling in the field (e.g., field data, surveys, or interviews or census data)

Types of data sources	**Secondary data**	Data types which were derived from other readily available information and not verified in the field (e.g., remote-sensed data, socioeconomic data, and mixed sources like databases like global statistics)
	Mixed data	Database (global statistics, e.g., map of carbon storage and FAO reports), bibliography, modeling, surveys, and field data.

Types of ES		Whether Ecosystem Services have been mentioned/identified in the article.
Provisioning		Products obtained from ecosystems, such as water, food, fiber, etc.
Regulating		Ecosystem services that regulate the environmental conditions in which human beings live (e.g., climate regulation, hydrological cycles, water quality)
Supporting		Basic ecosystem services that maintain the generation of all other ES (e.g., soil formation, pollination, nutrient cycling)
Cultural		Both tangible and intangible benefits derived from the ecosystem, such as recreation, aesthetics, spiritual benefits, and so on
Number of MES assessed	**In number**	At least one MES type should be studied: climate regulation, erosion control, water purification, air quality, pest regulation, etc.
Land use change type		Type of land use analyse or land use change has been mentioned
Relationship of ES and LUCC		How about the relationship of ES and LUCC

Relationship of ES and LUCC	**Evolution**	Those that analyze the temporal dynamics of ecosystem services (MES) and/or land use/land cover (LULC) based on three or more time points, in order to track long-term changes, transitions, or trends.
	Trade-offs/synergy	Refer to the relationships among multiple ecosystem services or between ES and LULC, where the increase in one service or land use outcome leads to the increase (synergy) or decrease (trade-off) in another.
	Drive	Refer to natural or anthropogenic factors that cause changes in ES and/or LULC, either directly or indirectly
	Impact	Refers to the observable effects or outcomes resulting from changes in land use/cover or ecosystem services, often expressed in terms of ecological degradation, service loss, or socio-economic consequences
	Evolution and Trade-off/synergy	
	Mixed	

	qualitative	Expressing the ES value with verbal terms
	quantitate	Expressing the ES values using tons/year/or/hectare
	Mix	
	Not indicated	

Approach	**Agent-based model**	An agent-based model (ABM) is a computational model for simulating the actions and interactions of autonomous agents (both individual or collective entities such as organizations or groups) in order to understand the behaviour of a system and what governs its outcomes.

	look-up tables	A kind of benefit transfer, which is based on national-scale assessment tables of ecosystem service values
	System dynamics	System dynamics (SD) is an approach to understanding the nonlinear behaviour of complex systems over time using stocks, flows, internal feedback loops, table functions and time delays
	Network analysis	Network analysis (NA) is a set of integrated techniques to depict relations among actors and to analyze the social structures that emerge from the recurrence of these relations
	Statistical analysis	such as correlation, were used to quantify the relationships in basis of conceptual models
	expert knowledge	To leverage the expertise of individuals with specialized knowledge to identify and solve problems
	Role play game	A role-playing game (sometimes spelled roleplaying game; abbreviated RPG) is a game in which players assume the roles of characters in a fictional setting. Players take responsibility for acting out these roles within a narrative, either through literal acting or through a process of structured decision-making regarding character development
	Participatory research	Participatory approaches (such as questionnaires, focus group) were increasingly used to elucidate the importance and contributions ecosystem services to human well-being.

Mode of assessment	**Evolution**	Those that analyze the temporal dynamics of ecosystem services (MES) and/or land use/land cover (LULC) based

		on three or more time points, in order to track long-term changes, transitions, or trends.
	Economic valuation	The process of assigning monetary value to ecosystem services, typically using methods such as market pricing, value transfer, willingness-to-pay, or cost–benefit analysis.
	Relationship	That means driving or impact or trade-offs relationship analysis
	Mapping	Studies showing the spatial distribution of the MES or LULC
	Mapping and Relationship	
	Mapping and Evolution	
	Mapping and Economic valuation	

Limitation	**Yes**	
	No	
Recommendations		
Limits to sustainability	**Yes**	Refer to the ecological, biophysical, or social thresholds beyond which continued land use or ecosystem service exploitation risks causing irreversible degradation or system collapse.
	No	
Scenarios/ Pathways	**Yes**	Scenarios describe possible future conditions under specific assumptions or policy settings, while pathways refer to the trajectories or sequences of changes leading toward those scenarios.
	No	

Challenges or gaps	**Yes**	Gaps refer to what is missing in current research, while challenges refer to what is difficult to achieve or address, even when recognized
	No	
Future research direction	**Yes**	Refer to the priority areas, approaches, and innovations that should be pursued in order to address current gaps and challenges and advance the field.
	No	
Main findings		Main finding or achievement of the article

6.1.2 Full-text screening list of the systematic review

Table 6.1-2 Full-text screening list of literature review (in English) -121 articles.

Year	Journal	Title	Author
2024	Sustainability	A Multi-Objective Scenario Study of County Land Use in Loess Hilly Areas: Taking Lintao County as an Example	
2024	Sustainability	Analysis of Spatial—Temporal Variation in Ecosystem Service Value in Shandong Province over the Last Two Decades	Ting Li 1, Donghui Shi 2, Shuguang Jiang 2 , Yu Li 2,* and Huilu Yu 1,*
2024	Open agriculture	Assessment and multi-scenario simulation of ecosystem service values in Southwest China's mountainous and hilly region	Bing Zhu, Yan Yang*, Yu Meng, Juan Chen
2024	Sustainability (switzerland)	Construction of the Ecological Security Pattern in Xishuangbanna Tropical Rainforest Based on Circuit Theory	Mengmeng Yan 1, Jilin Duan 1,*, Yubin Li 2, Yang Yu 3, Yu Wang 1, Jiawei Zhang 1 and Yu Qiu 1
2024	Scientific reports	Ecological protection makes the ecological Kuznets curve turning point come earlier	Xiaoyang Liu, Hongwei Wang, Songhong Li & Liyang Wang
2024	Global ecology and conservation	Ecological redline policy strengthens sustainable development goals through the strict protection of multiple ecosystem services	Lijuan Wang a, Hua Zheng b c, Yongzhe Chen d, Binbin Huang b c
2024	Sustainability	Ecological Security Patterns Research Based on Ecosystem Services and Circuit Theory in Southwest China	Qiang Wu 1 and Yunchuan Dai 2,

2024	Frontiers in forests and global change	Spatiotemporal response of ecosystem services to tourism activities in urban forests	Jiadan Li1, Xian Zhang1, Qing Gu2, Zhongchu Zhang3*, Kai Wang1 and Zhihao Xu1
2024	Water	The Impact of Major Ecological Projects on the Water Yield of Mountain Basins, Northern China	Xianglong Hou 1, Miwei Shi 1, Jianguo Zhao 2, Lingyao Meng 1, Yan Zhang 1, Rongzhi Zhang 1, Hui Yang 3,* and Jiansheng Cao 3,*
2023	Remote sensing	Analysis of Water Conservation Trends and Drivers in an Alpine Region: A Case Study of the Qilian Mountains	Junyu Sun 1, Chenrui Ni 1 and Mengmeng Wang 1,2,*
2023	Remote sensing	Assessing the Impact of Climate and Human Activities on Ecosystem Services in the Loess Plateau Ecological Screen, China	Changwen Wei 1 , Jiaqin Zeng 2,3,4, Jiping Wang 5, Xuebing Jiang 6, Yongfa You 7 , Luying Wang 1 , Yiming Zhang 1, Zhihong Liao 1 and Kai Su 1,3,*
2023	Frontiers in earth science	Assessing the impacts of future urban expansion on multiple ecosystem services in the transnational area of Changbai Mountain	Ruikang Chen, Da Zhang*, Ying Nan, Hengdong Feng* and Xin Geng
2023	Ecologica l indicators	Assessment and prediction of carbon storage based on land use/land cover dynamics in the coastal area of Shandong Province	Huiling Zheng a, Huifeng Zh eng b
2023	Ecologica l indicators	Constructing ecological security patterns based on ecosystem services trade-offs and ecological sensitivity: A case study of Shenzhen metropolitan area, China	Xiaoyang Liu,Yan Su,Zhigang Li,Sen Zhang
2023	Sustainabi lity	Evaluation of the Impacts of Change in Land Use/Cover on Carbon Storage in Multiple Scenarios in the Taihang Mountains, China	Huanchao Guo,Shi He,Haitao Jing,Geding Yan, Hui Li
2023	Internatio nal journal of environm ental research and public health	Evolution of Habitat Quality and Its Response to Topographic Gradient Effect in a Karst Plateau: A Case Study of the Key Biodiversity Conservation Project Area of Wuling Mountains	Bo Xie 1, Shunbing Meng 1 and Mingming Zhang
2023	Internatio nal journal of environm ental research and	How Urban Fringe Expansion Affects Green Habitat Diversity? Analysis from Urban and Local Scale in Hilly City	Bo Xie 1, Shunbing Meng 1 and Mingming Zhang 1,2,*

	public health		
2023	Forests	Identification of Ecological Security Patterns for the Qiandongnan Ecotourism Area in Southwest China Using InVEST and Circuit Theory	Jiatong Li,Yang Liu,Arni Abdul Gani, Jianli Wu, Yunchuan Dai
2023	Remote sensing	Identifying the Driving Impact Factors on Water Yield Service in Mountainous Areas of the Beijing-Tianjin-Hebei Region in China	Hui Yang,Xianglong Hou, Jiansheng Cao
2023	Land	Impact of Ecological Restoration Project on Water Conservation Function of Qilian Mountains Based on InVEST Model-A Case Study of the Upper Reaches of Shiyang River Basin	Jiarui Wang,Junju Zhou,Dongfeng Ma,Xi Zhao,Wei Wei,Chunfang Liu,Dongxia Zhang, Chunli Wang
2023	Land	Multiscale analysis of the Impact of landscape Pattern on the trade-off and Synergy of Ecosystem services in southern Zhejiang	Lilian Ding,Yan Liao,Congmou Zhu,Qiwei Zheng, Ke Wang
2023	Ecologica l indicators	Scenario analysis and relative importance indicators for combined impact of climate and LULC change on annual ecosystem services in the Karst mountainous region	Luqian Li，Erqi Xu
2023	Forests	Spatio-Temporal Changes and Trade-Offs/Synergies among Ecosystem Services in Beijing from 2000 to 2020	Fang Xu,Shige Chen,Xiyue Wang and Xiangrong Wang
2023	Land	Spatio-Temporal Variation of the Ecosystem Service Value in Qilian Mountain National Park (Gansu Area) Based on Land Use	Lili Pu ,Chengpeng Lu 2,,Xuedi Yang 1 andXingpeng Chen
2023	Remote sensing	Spatiotemporal Changes in Supply-Demand Patterns of Carbon Sequestration Services in an Urban Agglomeration under China's Rapid Urbanization	Wenhai Hong 1,2,†, Guangdao Bao 3,† , Yunxia Du 4, Yujie Guo 1,2, Chengcong Wang 1,2, Guodong Wang 1,2 and Zhibin Ren 1,2,*
2023	Land	Study on the Ecosystem Service Supply-Demand Relationship and Development Strategies in Mountains in Southwest China Based on Different Spatial Scales	Yahui Wang 1,2 , Erfu Dai 2,3,*, Yue Qi 1 and Yao Fan 1
2022	Ecologica l indicators	An integrated approach to constructing ecological security patterns and identifying ecological restoration and protection areas: A case study of Jingmen, China	
2022	Remote sensing	Assessing the Impact of Urbanization and Eco-Environmental Quality on Regional Carbon Storage: A	Lu Niu 1 , Zhengfeng Zhang 1, Yingzi Liang 2 and Yanfen Huang 1,*

		Multiscale Spatio-Temporal Analysis Framework	
2022	Open geosciences	Changes in landscape pattern and ecological service value as land use evolves in the Manas River Basin	Yongjun Du, Xinlin He*, Xiaolong Li*, Xiaoqian Li, Xinchen Gu, Guang Yang, Wanjing Li, Yage Wu, and Jun Qiu
2022	International journal of environmental research and public health	Construction and Optimization of an Ecological Security Pattern Based on the MCR Model: A Case Study of the Minjiang River Basin in Eastern China	
2022	Land	Ecosystem and Driving Force Evaluation of Northeast Forest Belt	Zhihong Liao 1,† , Kai Su 1,*,† , Xuebing Jiang 2, Xiangbei Zhou 1, Zhu Yu 3, Zhongchao Chen 4, Changwen Wei 1 , Yiming Zhang 1 and Luying Wang
2022	Remote sensing	Effects of Land Use/Cover on Regional Habitat Quality under Different Geomorphic Types Based on InVEST Model	Baixue Wang 1,2 and Weiming Cheng
2022	Ecology and evolution	Potential impact of LULC change on habitat quality in the distribution range of crocodile lizards in China	Xiaoli Zhang, Xudong Qin, Facundo Alvarez, Zening Chen, Zhengjun Wu
2022	Sustainability	Spatial and Temporal Differentiation of Mountain Ecosystem Service Trade-Offs and Synergies: A Case Study of Jieshi Mountain, China	Guangzi Li and Jun Cai
2022	Land	Spatial Divergence Analysis of Ecosystem Service Value in Hilly Mountainous Areas: A Case Study of Ruijin City	Hualin Xie *,Zhenhong Zhu andZhe Li
2022	Frontiers in ecology and evolution	Spatial-temporal dynamics and evolution of ecological security in a rapid urbanization city, Southwest China	Yunchuan Dai，Yuying Diao，Chongyang Dai，Yi Li，Guiyan Sun，Babar Zahoor，Dayong Li
2022	Water	Spatial-Temporal Pattern Analysis of Land Use and Water Yield in Water Source Region of Middle Route of South-to-North Water Transfer Project Based on Google Earth Engine	Pengtao Niu 1,2,Enchao Zhang 3,Yu Feng 1 andPeihao Peng
2022	Sustainability	Spatially Heterogeneity Response of Critical Ecosystem Service Capacity to Address Regional Development Risks to Rapid Urbanization: The Case of Beijing-Tianjin-Hebei Urban Agglomeration in China	Kaiping Wang, Weiqi Wang, Niyi Zha, Yue Feng, Chenlan Qiu, Yunlu Zhang *, Jia Ma * and Rui Zhang

2022	Sustainability (switzerland)	Spatiotemporal Evolution of Ecosystem Services in the Wanhe Watershed Based on Cellular Automata (CA)-Markov and InVEST Models	Cheng Zhong, Yiming Bei, Hongliang Gu * and Pengfei Zhang
2022	Journal of geographical sciences	The response of key ecosystem services to land use and climate change in Chongqing: Time, space, and altitude	GAO Jie1,2,3, *BIAN Hongyan1,2, ZHU Chongjing1, TANG Shuang1
2022	Remote sensing	Unraveling the Spatio-Temporal Relationship between Ecosystem Services and Socioeconomic Development in Dabie Mountain Area over the Last 10 Years	Jianfeng Liu 1,2,3, Lin Chen 1,3, Zhonghua Yang 1,3, Yifan Zhao 2 and Xiwang Zhang 2,4,*
2022	Water supply	Water conservation capacity under climate and land use change scenarios in Changbai Mountain, China	Wenhao Sun a,b, Jianmin Biana,b,*, Yihan Lia,b and Jialin Lia,b
2021	Sustainability	Spatio-Temporal Changes of Land-Use/Land Cover Change and the Effects on Ecosystem Service Values in Derong County, China, from 1992-2018	Wang, Yanru; Zhang, Xiaojuan; Peng, Peihao
2021	Forests	The Influence of Land Use Change on Key Ecosystem Services and Their Relationships in a Mountain Region from Past to Future (1995-2050)	Gao, Jie; Tang, Xuguang; Lin, Shiqiu; Bian, Hongyan
2021	Science Of The Total Environment	Identifying the spatial disparities and determinants of ecosystem service balance and their implications on land use optimization	Jiang, Chong; Yang, Zhiyuan; Wen, Meili; Huang, Li; Liu, Haimeng; Wang, Jun; Chen, Weilian; Zhuang, Changwei
2021	Ecological Indicators	Changes in ecosystem services in a montane landscape impacted by major earthquakes: A case study in Wenchuan earthquake-affected area, China	Duan, Yanan; Di, Baofeng; Ustin, Susan L.; Xu, Chong; Xie, Qiang; Wu, Shaolin; Li, Jierui; Zhang, Ruixing
2021	International Journal Of Environmental Research And Public Health	Spatiotemporal Changes of Ecosystem Service Value Determined by National Land Space Pattern Change: A Case Study of Fengdu County in The Three Gorges Reservoir Area, China	Zhang, Haozhe; Yang, Qingyuan; Zhang, Zhongxun; Lu, Dan; Zhang, Huiming
2021	Catena	Spatial heterogeneity of ecosystem services and their trade-offs in the Hengduan Mountain region, Southwest China	Wang, Yahui; Dai, Erfu; Ge, Quansheng; Zhang, Xianzhou; Yu, Chengqun
2021	Science Of The Total	Integrating supply and demand factors for estimating ecosystem services scarcity value and its response to	Shi, Yu; Feng, Chen-Chieh; Yu, QianRu; Guo, Luo

	Environment	urbanization in typical mountainous and hilly regions of south China	
2021	Land	Qualifying Land Use and Land Cover Dynamics and Their Impacts on Ecosystem Service in Central Himalaya Transboundary Landscape Based on Google Earth Engine	Gu, Changjun; Zhang, Yili; Liu, Linshan; Li, Lanhui; Li, Shicheng; Zhang, Binghua; Cui, Bohao; Rai, Mohan Kumar
2021	Forests	InVEST Model-Based Spatiotemporal Analysis of Water Supply Services in the Zhangcheng District	Liu, Run; Niu, Xiang; Wang, Bing; Song, Qingfeng
2021	Frontiers In Environmental Science	Identifying Critical Area of Ecosystem Service Supply and Demand at Different Scales Based on Spatial Heterogeneity Assessment and SOFM Neural Network	Liao, Guitang; He, Peng; Gao, Xuesong; Lin, Zhengyu; Fang, Conggang; Zhou, Wei; Xu, Chenghua; Deng, Liangji
2021	Sustainability	Evaluation on the Change Characteristics of Ecosystem Service Function in the Northern Xinjiang Based on Land Use Change	Wang, Yang; Shataer, Remina; Xia, Tingting; Chang, Xueer; Zhen, Hui; Li, Zhi
2021	Land	Delimitating the Ecological Spaces for Water Conservation Services in Jilin Province of China	Wang, Huan; Zhang, Chao; Li, Li; Yun, Wenju; Ma, Jiani; Gao, Lulu
2021	Journal Of Environmental Management	Integrating ecosystem services and landscape ecological risk into adaptive management: Insights from a western mountain-basin area, China	Gong, Jie; Cao, Erjia; Xie, Yuchu; Xu, Caixian; Li, Hongying; Yan, Lingling
2021	International Journal Of Environmental Research And Public Health	Factors of the Ecosystem Service Value in Water Conservation Areas Considering the Natural Environment and Human Activities: A Case Study of Funiu Mountain, China	Guo, Chunyang; Gao, Jianhua; Zhou, Boyan; Yang, Jie
2021	Journal Of Environmental Management	Labor force transfer, vegetation restoration and ecosystem service in the Qilian Mountains	Zhang, Jian; Zhao, Xu-Zhe; Zhou, Rui; Tian, Tao; Cui, Jin-Ying; Zhao, Ling; Wang, Geng-Rui; Xiong, You-Cai
2021	Journal Of Cleaner Production	Regional differences of water regulation services of terrestrial ecosystem in the Tibetan Plateau: Insights from multiple land covers	Zhang Yongyong; Hou Jinjin; Ma Guoxia; Zhai Xiaoyan; Lv Aifeng; Wang Wei; Wang Zhonggen
2021	Resources Conservation And Recycling	Multilevel modelling of impacts of human and natural factors on ecosystem services change in an oasis, Northwest China	Li, Zhihui; Xia, Jun; Deng, Xiangzheng; Yan, Haiming

2021	Ecological Indicators	Evolution of habitat quality and association with LULC changes in mountainous areas: A case study of the Taihang Mountains in Hebei Province, China	Yang, Yuanyuan
2021	Remote Sensing	Application of Ecosystem Service Bundles and Tour Experience in Land Use Management: A Case Study of Xiaohuangshan Mountain (China)	Zhao, Qiqi; Chen, Yanming; Cuan, Yuda; Zhang, Han; Li, Wei; Wan, Sida; Li, Manchun
2021	Sustainability	Impacts of LULC Change on Ecosystem Service Value of Mountain-Oasis-Desert Ecosystem: A Case Study of Kaidu-Kongque River Basin, Northwest China	Mamat, Aynur; Wang, Jianping; Ma, Yuanxu
2021	Land Use Policy	Dynamics of spatial relationships among ecosystem services and their determinants: Implications for land use system reform in Northwestern China	Lyu, Rongfang; Clarke, Keith C.; Zhang, Jianming; Feng, Junli; Jia, Xuehui; Li, Jijun
2021	Land Degradation & Development	Spatiotemporal investigation of the interactive coercing relationship between urbanization and ecosystem services in arid northwestern China	Shi, Lei; Halik, Umut; Mamat, Zulpiya; Aishan, Tayierjiang; Abliz, Abdulla; Welp, Martin
2021	Journal Of Arid Land	Response of ecosystem service value to land use/cover change in the northern slope economic belt of the Tianshan Mountains, Xinjiang, China	Sun Chen; Ma Yonggang; Gong Lu
2021	Remote Sensing	Remotely Sensed Ecological Protection Redline and Security Pattern Construction: A Comparative Analysis of Pingtan (China) and Durban (South Africa)	Lin, Qixin; Eladawy, Ahmed; Sha, Jinming; Li, Xiaomei; Wang, Jinliang; Kurbanov, Eldar; Thomas, Abraham
2021	Sustainability	Trade-Offs and Synergies of Multiple Ecosystem Services for Different Land Use Scenarios in the Yili River Valley, China	Shi, Mingjie; Wu, Hongqi; Fan, Xin; Jia, Hongtao; Dong, Tong; He, Panxing; Baqa, Muhammad Fahad; Jiang, Pingan
2021	Land Degradation & Development	Environmental determinants impacting the spatial heterogeneity of karst ecosystem services in Southwest China	Gao, Jiangbo; Zuo, Liyuan; Liu, Wanlu
2021	International Journal Of Environmental Research And Public Health	Gray forecast of ecosystem services value and its driving forces in karst areas of china: A case study in guizhou province, China	Pan, S.; Liang, J.; Chen, W.; Li, J.; Liu, Z.
2021	Sustainability	Identifying and Zoning Key Areas of Ecological Restoration for Territory in	Zhang, Can; Fang, Shiming

		Resource-Based Cities: A Case Study of Huangshi City, China	
2020	Science Of The Total Environment	Land use transitions and the associated impacts on ecosystem services in the Middle Reaches of the Yangtze River Economic Belt in China based on the geo-informatic Tupu method	Chen, Wanxu; Zhao, Hongbo; Li, Jiangfeng; Zhu, Lijun; Wang, Zheye; Zeng, Jie
2020	Journal Of Cleaner Production	Spatial-temporal changes in ecosystem services and the trade-off relationship in mountain regions: A case study of Hengduan Mountain region in Southwest China	Wang, Yahui; Dai, Erfu
2020	Science Of The Total Environment	Identification of ecosystem service bundles and driving factors in Beijing and its surrounding areas	Chen, Tianqian; Feng, Zhe; Zhao, Huafu; Wu, Kening
2020	Journal Of Cleaner Production	Spatio-temporal quantification of patterns, trade-offs and synergies among multiple hydrological ecosystem services in different topographic basins	Sun, Xiaoyin; Shan, Ruifeng; Liu, Fei
2020	Sustainability Science	Integrated assessment of land-use/coverage changes and their impacts on ecosystem services in Gansu Province, northwest China: implications for sustainable development goals	Liu, Lijun; Liang, Youjia; Hashimoto, Shizuka
2020	Sustainability	Quantitative Assessment of the Relative Impacts of Land Use and Climate Change on the Key Ecosystem Services in the Hengduan Mountain Region, China	Dai, Erfu; Yin, Le; Wang, Yahui; Ma, Liang; Tong, Miao
2020	Environmental Science And Pollution Research	Research on recognition and protection of ecological security patterns based on circuit theory: a case study of Jinan City	Huang, Jiuming; Hu, Yecui; Zheng, Fangyu
2020	International Journal Of Environmental Research And Public Health	Impact of Fast Urbanization on Ecosystem Health in Mountainous Regions of Southwest China	Xiao, Yi; Guo, Luo; Sang, Weiguo
2020	Global Ecology And Conservation	Impacts of the grain for Green Program on the spatial pattern of land uses and ecosystem services in mountainous settlements in southwest China	Fan, Min; Xiao, Yu-ting

2020	Sustainability	Trade-Offs Analysis of Ecosystem Services for the Grain for Green Program: Informing Reforestation Decisions in a Mountainous Headwater Region, Northeast China	Li, Xiufen; Tian, Yichen; Gao, Tian; Jin, Lei; Li, Shuangtian; Zhao, Dan; Zheng, Xiao; Yu, Lizhong; Zhu, Jiaojun
2020	Sustainability	The Impact of Land Use Change on Ecosystem Service Value in the Upstream of Xiong'an New Area	Wang, Zhiyin; Cao, Jiansheng; Zhu, Chunyu; Yang, Hui
2019	Journal Of Forestry Research	The influence of land use change on the spatial-temporal variability of habitat quality between 1990 and 2010 in Northeast China	Dai, Limin; Li, Shanlin; Lewis, Bernard J.; Wu, Jian; Yu, Dapao; Zhou, Wangming; Zhou, Li; Wu, Shengnan
2019	Science Of The Total Environment	A multiscale analysis of urbanization effects on ecosystem services supply in an urban megaregion	Wang, Jiali; Zhou, Weiqi; Pickett, Steward T. A.; Yu, Wenjuan; Li, Weifeng
2019	Ecological Indicators	Quantifying and mapping the responses of selected ecosystem services to projected land use changes	Lang, Yanqing; Song, Wei
2019	Journal Of Geographical Sciences	Integration of InVEST-habitat quality model with landscape pattern indexes to assess mountain plant biodiversity change: A case study of Bailongjiang watershed in Gansu Province	Gong Jie; Xie Yuchu; Cao Erjia; Huang Qiuyan; Li Hongying
2019	Ecological Indicators	Tradeoffs/synergies of multiple ecosystem services based on land use simulation in a mountain-basin area, western China	Gong, Jie; Liu, Dongqing; Zhang, Jinxi; Xie, Yuchu; Cao, Erjia; Li, Hongying
2019	Mitigation And Adaptation Strategies For Global Change	Assessing the high impacts of land use change: spatial characteristics of land uses and ecological compensation based on payment for ecosystem services model in a mountainous area, China	Fan, Min; Chen, Li; Wang, Qing
2019	Global Ecology And Conservation	Spatio-temporal variation in grassland degradation and its main drivers, based on biomass: Case study in the Altay Prefecture, China	Zhang, Guangpeng; Yan, Junjie; Zhu, Xiaotong; Ling, Hongbo; Xu, Hailiang
2019	Sustainability	The Construction of a Regional Ecological Security Pattern Based on Circuit Theory	Li, Jiulin; Xu, Jiangang; Chu, Jinlong
2019	Science Of The Total Environment	Estimates of shifts in ecosystem service values due to changes in key factors in the Manas River basin, northwest China	Ling, Hongbo; Yan, Junjie; Xu, Hailiang; Guo, Bin; Zhang, Qingqing
2019	Ecological Indicators	Land use/land cover changes and its impact on ecosystem services in ecologically fragile zone: A case study	Huang, An; Xu, Yueqing; Sun, Piling; Zhou, Guiyao;

		of Zhangjiakou City, Hebei Province, China	Liu, Chao; Lu, Longhui; Xiang, Ying; Wang, Hui
2019	Journal Of Mountain Science	What is the relationship between ecosystem services and urbanization? A case study of the mountainous areas in Southwest China	Peng Li; Wang Xu-xi
2019	Applied Ecology And Environmental Research	Effect of land creation on regional ecological environment: a case study for Lanzhou city, China	Shi, Y. F.; Ma, C.; Kong, D. J.; Zhao, J.
2019	Journal Of Geographical Sciences	The effects of urbanization on ecosystem services for biodiversity conservation in southernmost Yunnan Province, Southwest China	Cheng Fangyan; Liu Shiliang; Hou Xiaoyun; Wu Xue; Dong Shikui; Coxixo, Ana
2019	Sustainability	Integrating Biophysical and Sociocultural Methods for Identifying the Relationships between Ecosystem Services and Land Use Change: Insights from an Oasis Area	Wei, Hejie; Fan, Weiguo; Lu, Nachuan; Xu, Zihan; Liu, Huiming; Chen, Weiqiang; Ulgiati, Sergio; Wang, Xuechao; Dong, Xiaobin
2018	Journal Of Geographical Sciences	Modeling the spatio-temporal changes in land uses and its impacts on ecosystem services in Northeast China over 2000-2050	Xia Tian; Wu Wenbin; Zhou Qingbo; Tan Wenxia; Verburg, Peter H.; Yang Peng; Ye Liming
2018	Science Of The Total Environment	Linking ecosystem services and circuit theory to identify ecological security patterns	Peng, Jian; Yang, Yang; Liu, Yanxu; Hu, Yi'na; Du, Yueyue; Meersmans, Jeroen; Qiu, Sijing
2018	Sustainability	Tipping Points in the Supply of Ecosystem Services of a Mountainous Watershed in Southeast Asia	Thellmann, Kevin; Cotter, Marc; Baumgartner, Sabine; Treydte, Anna; Cadisch, Georg; Asch, Folkard
2018	Journal Of Geographical Sciences	Ecosystem assessment and protection effectiveness of a tropical rainforest region in Hainan Island, China	Zhai, Jun; Hou, Peng; Cao, Wei; Yang, Min; Cai, Mingyong; Li, Jing
2018	Sustainability	Evaluation of the Effects of Land Cover Change on Ecosystem Service Values in the Upper Reaches of the Heihe River Basin, Northwestern China	Zhao, Minmin; He, Zhibin
2018	Ecosystem Services	Land use/land cover change and the effects on ecosystem services in the Hengduan Mountain region, China	Wang, Yahui; Dai, Erfu; Yin, Le; Ma, Liang
2018	Biological Conservation	Strengthening protected areas for giant panda habitat and ecosystem services	Zhang, Jingjing; Xu, Weihua; Kong, Lingqiao; Hull, Vanessa; Xiao, Yi; Xiao, Yang; Ouyang, Zhiyun

2018	Ecological Complexity	The impact of mining changes on surrounding lands and ecosystem service value in the Southern Slope of Qilian Mountains	Qian Dawen; Yan Changzhen; Xiu Lina; Feng Kun
2018	Global Change Biology	Warming and land use change concurrently erode ecosystem services in Tibet	Hopping, Kelly A.; Knapp, Alan K.; Dorji, Tsechoe; Klein, Julia A.
2018	Scientific Reports	Scenario analysis of ecosystem service changes and interactions in a mountain-oasis-desert system: a case study in Altay Prefecture, China	Fu, Qi; Hou, Ying; Wang, Bo; Bi, Xu; Li, Bo; Zhang, Xinshi
2018	Sustainability	Changes of Ecosystem Services and Landscape Patterns in Mountainous Areas: A Case Study in the Mentougou District in Beijing	Yi, Yang; Shi, Mingchang; Liu, Chunjiang; Wang, Bin; Kang, Hongzhang; Hu, Xinli
2018	Sustainability	Land Use and Land Cover Dynamics and Assessing the Ecosystem Service Values in the Trans-Boundary Gandaki River Basin, Central Himalayas	Rai, Raju; Zhang, Yili; Paudel, Basanta; Acharya, Bipin Kumar; Basnet, Laxmi
2018	Land Use Policy	Effects of China's payment for ecosystem services programs on cropland abandonment: A case study in Tiantangzhai Township, Anhui, China	Zhang, Qi; Song, Conghe; Chen, Xiaodong
2017	Forests	Assessing Ecosystem Services in Rubber Dominated Landscapes in South-East Asia-A Challenge for Biophysical Modeling and Transdisciplinary Valuation	Thellmann, Kevin; Blagodatsky, Sergey; Haeuser, Inga; Liu, Hongxi; Wang, Jue; Asch, Folkard; Cadisch, Georg; Cotter, Marc
2017	Ecological Indicators	Modeling changes in land use patterns and ecosystem services to explore a potential solution for meeting the management needs of a heritage site at the landscape level	You, W.; Ji, Z.; Wu, L.; Deng, X.; Huang, D.; Chen, B.; Yu, J.; He, D.
2017	Sustainability	Ecosystem Services Value Assessment and Uneven Development of the Qingjiang River Basin in China	Lin, Zhengsong; Ye, Xinyue; Wei, Qian; Xin, Fan; Lu, Zhang; Kudva, Sonali; Dai, Qiwen
2017	Science Of The Total Environment	Effects of land use and climate change on ecosystem services in Central Asia's arid regions: A case study in Altay Prefecture, China	Fu, Qi; Li, Bo; Hou, Ying; Bi, Xu; Zhang, Xinshi
2016	Journal Of The Indian Society Of Remote Sensing	Effects of the Land Use Change on Ecosystem Service Value in Chengdu, Western China from 1978 to 2010	Peng, Wen F.; Zhou, Jie M.; Fan, Shu Y.; Yang, Cun J.
2016	Energies	Responses of Ecosystem Service to Land Use Change in Qinghai Province	Han, Ze; Song, Wei; Deng, Xiangzheng

2016	Environmental Earth Sciences	Effects of LULC intensity on ecosystem services and human well-being: a case study in Huailai County, China	Xu, Ying; Tang, Haiping; Wang, Bojie; Chen, Jiao
2016	Ecosystem Services	Ecosystem service status and changes of degraded natural reserves - A study from the Changbai Mountain Natural Reserve, China	Yu, Dandan; Han, Shijie
2015	Applied Ecology And Environmental Research	Dynamics of ecosystem service values in response to landscape pattern changes from 1995 to 2005 in Guangzhou, southern China	Ye, Yanqiong; Zhang, Jia'en; Chen, Lili; Ouyang, Ying; Parajuli, Prem
2015	Sustainability	Ecosystem Services Evaluation and Its Spatial Characteristics in Central Asia's Arid Regions: A Case Study in Altay Prefecture, China	Fu, Qi; Li, Bo; Yang, Linlin; Wu, Zhilong; Zhang, Xinshi
2012	Applied Geography	Characterizing landscape pattern and ecosystem service value changes for urbanization impacts at an eco-regional scale	Su, Shiliang; Xiao, Rui; Jiang, Zhenlan; Zhang, Yuan
2012	Environmental Monitoring And Assessment	Impact of socioeconomic development on ecosystem services and its conservation strategies: a case study of Shandong Province, China	Wang, Shujun; Liu, Jian; Wang, Renqing; Ni, Zirong; Xu, Shipeng; Sun, Yueyao
2009	Ambio	Ecosystem Services Assessment of Two Watersheds of Lancang River in Yunnan, China with a Decision Tree Approach	Wang, Chongyun; van der Meer, Peter; Peng, Mingchun; Douven, Wim; Hessel, Rudi; Dang, Chenlin
2007	Environmental Monitoring And Assessment	Quantification of the impact of LULC changes on ecosystem services: A case study in Pingbian County, China	Li, Ren-Qiang; Dong, Ming; Cui, Jian-Yong; Zhang, Li-Li; Cui, Qing-Guo; He, Wei-Ming

Table 6.1-3 Full-text screening list of literature review (in Chinese) -82 articles

Year	Journal	Title of the paper	Authors
2024	Journal of Guizhou Normal University (Natural Science Edition 贵州师范大学学报(自然科学版	Construction of ecological security pattern in karst mountains in southeast Yunnan: A case study of Wenshan Prefecture 滇东南喀斯特山区生态安全格局构建 ———以文山州为例	刘凤莲 1 ，2 ，刘艳 1 ，吉冠秋 1 ，杜汶胶 3
2024	Bulletin of Soil and Water Conservation	EcosystemType Rcoe gnitionand Satiotemp poral Pttern Ca hange Analysis BasedonRealms-Biomes-EcosystemClassification—A Case Study of Taihang Mountains AeainHebei Province 基于域—生物群系—功能群分类的生态系统类型识别及时空格局变化分析———以河北省太行山区为例	毕善婷 1,陈影 1,3,李泽 2,屈爽 2,赵文超 2,梁阅兵 2
2024	Enviromnental science	Spatio-temporal Evolution and Trade-off/Synergy Analysis of Ecosystem Services in Regions of Rapid Urbanization： A Case Study of the Lower Yellow River Region 快速城镇化地区生态系统服务时空演变及权衡协同分析：以黄河下游地区为例	李欣， 陈登帅*， 张冰冰， 曹建荣 *
2024	Acta Ecologica Sinica	Quantifying relative contribution of climate change and land use change to the change of ecological assets: taking Fangshan District as an example 量化气候和土地利用变化对生态资产变化的相对贡献———以房山区为例	王鹤潭 1，巩贺 2，黄玫 2，张远东 3，孙玮 1，顾峰雪 1，
2024	Journal of Agricultural Resources and Environment	The driving factors of ecosystem services and their tradeoffs in the Manas River basin of Xinjiang,China 玛纳斯河流域生态系统服务及其权衡关系的驱动因素	殷丽雪 1，徐晓龙 1，胡保安 2，刘璐铭 1，王新军 3，贾宏涛 3*
2024	Research of Soil and Water Conversation	Spatio-temporal Changes and Tade-offs of Eosystem Service Value in Mountain-	高春莲 1,2,胡宝清 1,黄思敏 1,2,黄

		River-Sea Cuopling Key Zone Rsearch 山江海耦合关键带生态系统服务价值时空变化及其权衡研究	丽芳 1,2,李彩茶 1,2
2024	Ecology and Environmental Sciences	Research on zoning of ecological conservation importance and its spatio-temporal differentiation of habitat status over a long time sequence: A case study in Guangdong province 生态保护重要性分区及其长时间序列生境状况时空分异研究 ——以广东省为例	向男, 王明旭, 张宏锋, 廖宝淦
2023	Acta Ecologica Sinica	Identification and optimization of ecological security pattern in the Chengdu-Chongqing Economic Zone 成渝地区双城经济圈生态安全格局识别及改善对策	林文豪 1，2， 温兆飞 1，*，吴胜军 1， 毕月
2023	Research of Soil and Water Conversation	Identification and Rstoration Sratetgy of Key Areasof Eolocgical Restorationin Urban Agglomeration Around Poyang Lake Basedon Eoloc gical Scuritey Pattern 基于生态安全格局的环鄱阳湖城市群生态恢复重点区域识别与修复策略	张海铃,叶长盛,胡梦姗
2023	Journal of Environmental Engineering Technology	The impact of land use change on ecosystem service value in karst mountain area 喀斯特山区土地利用变化对生态系统服务价值的影响	李文芳，任晓冬*，刘弋菱，王霄念，肖杰
2022	Resources & Industries	Spatial pattern and dynamic evolution of ecosystem service value in Huoshan County from 1990 to 2020 1990-2020 年霍山县生态系统服务价值空间格局及其动态演化	方林 1，蔡俊 1，刘艳晓 2，杨波
2022	Acta Ecologica Sinica	Ecosystem service tradeoff/synergistic effect of land use change in "mountain-oasis-desert" complex system: A case study of Zhangye City “山地-绿洲-荒漠”复合系统土地利用变化的生态系统服务权衡/协同效应——以张掖市为例	姚礼堂，张学斌，周亮，罗君，王梓洋，雷越，李意霞

2022	Journal of Environmental Engineering Technology 环境工程技术学报	Effects of land use change on ecosystem service value in karst mountainous area 喀斯特山区土地利用变化对生态系统服务价值的影响	李文芳，任晓冬*，刘弋菱，王霄念，肖杰
2022	Research of Soil and Water Conversation	Evolution of ecosystem service value in Kunyu Mountain National Nature Reserve 昆嵛山国家级自然保护区生态系统服务价值演变	张文馨 1，范小莉 1，王强 2，房用 1，时良 3，梁玉
2022	Research of Environmental Sciences	Evolution and Scenario Prediction of Ecosystem Service Value in Dalou Mountain Area 大娄山地区生态系统服务价值演变与情景预测	姜栋栋 1,3，杨帆 4，马伟波 2*，李海东 2，张龙江 2，刘桂建
2022	Acta geographica sinica	The spatio-temporal pattern and functional zoning of ecosystem services in the karst mountainous area of southeastern Yunnan 滇东南喀斯特山区生态系统服务时空格局及功能分区	赵筱青 1，石小倩 1，李驭豪 1，李益敏 1，黄佩 1,2
2022	Journal of Shaanxi Normal University (Natural Science edition) 陕西师范大学学报（自然科学版	Effects of human activities on ecosystem quality in Qinling -Daba Mountains: a case study of Hanzhong city 秦巴山区人类活动对生态系统质量的影响———以汉中市为例	郑碧军，刘晓芳，周忠学
2022	Chinese Journal of Eco-Agriculture	Cold/hot spots identification and tradeoff/synergy analysis of ecosystem services in Taihang Mountain area 太行山区生态系统服务冷热点区域识别及其权衡/协同关系分析	高会 1, 付同刚 1, 梁红柱 2, 刘金铜 1
2022	Resources and Environment in the Yangtze Basin	The trade-off/synergy relationship of ecosystem services in Wenshan City, Yunnan Province 云南省文山市生态系统服务的权衡/协同关系	李益敏 1，李驭豪 1，赵筱青 1*，普军伟 2，王茜 1，谭琨 1，苗培培 1，杨一铭 1
2022	Bulletin of Soil and Water Conservation	Effects of Land Use Transition on Ecosystem service values in Wuling Mountain Region in Chongqing City	张传华 1，周苗 1，刘力 1，王钟

		重庆市武陵山区土地利用转型对生态系统服务价值的影响	书 2 ， 邓炜 1 ， 3
2020	Transactions of the Chinese Society of Agricultural Engineering 农 业 工 程 学 报	Gradient effects of ecosystem services and ecological zoning in the Beijing Bay Transition zone 北京湾过渡带生态系统服务梯度效应分析及生态分区	刘晓娜，刘春兰，陈龙，裴 厦，乔青
2019	Journal of Beijing Forestry University 北 京 林 业 大 学 学 报	Green space planning framework based on ecosystem service simulation: A case study of shallow mountainous area in Beijing 基于生态系统服务功能模拟演算的绿色空间规划框架——以北京市浅山区为例	李方正，刘阳，施瑶胡凯富，郑曦
2020	Journal of Shaanxi Normal University (Natural Science edition) 陕西师范大学学报（自然科学版	Effects of land use change on agro-ecosystem services in Qinling-Dabashan Mountains: A case study of Hanzhong Basin 秦巴山区土地利用变化对农业生态系统服务的影响———以汉中盆地为例	张碧桃，周忠学＊
2007	JOURNAL OF DESERT RESEARCH	The effect of oasis land use/coverage on the value of the service value in the oasis - desert system 干旱区典型山地-绿洲-荒漠系统中绿洲土地利用/覆盖变	黄青, 孙洪波, 王让会, 张慧芝

		化对生态系统服务价值的影响	
2010	CHINA POPULATION□RESOURCES AND ENVIRONMENT	Ecological service value of Shiyang River Basin based on land use 基于土地利用的石羊河流域生态服务价值	蒋小荣，李丁，李智勇
2010	RESOURCES SCIENCE	Response of ecological service value to land use change in Beijing from 1988 to 2005 1988 年至 2005 年北京生态服务价值对土地利用变化的响应	
2013	JOURNAL OF BASIC SCIENCE AND ENGINEERING	Dynamic evolution of ecological service value in Loess hilly area based on LUCC 基于 LUCC 的黄土丘陵区生态服务价值动态演变研究	张文海，赵阳，余新晓，刘旭辉，贾剑波，孙佳美
2015	China water and water conservation	Study on ecological service value of Jihe River Basin based on land use change 基于土地利用变化的藉河流域生态服务价值研究	王友生 1，2，余新晓 1，王多尧 3，李庆云 1
2018	Chinese Journal of Applied Ecology	Topographic gradient effect of ecosystem service value in the middle reaches of the Yangtze River	

		长江中游地区生态系统服务价值的地形梯度效应	
2 0 2 2	Resources & Industries	Spatial pattern and dynamic evolution of ecosystem service value in Huoshan County from 1990 to 2020 1990-2020 年霍山县生态系统服务价值空间格局及其动态演化	方林 1，蔡俊 1，刘艳晓 2，杨波
2021	Ecological Science	Spatial-temporal changes of landscape pattern and ecosystem service value in Xiannusan Resort Town, Chongqing 重庆市仙女山度假小镇景观格局及生态系统服务价值时空演变	秦普艳 1, 胡志毅 1,*, 管陈雷 2, 张柳柳 1
2022	Acta Ecologica Sinica	Ecosystem service tradeoff/synergistic effect of land use change in "mountain-oasis-desert" complex system: A case study of Zhangye City “山地-绿洲-荒漠”复合系统土地利用变化的生态系统服务权衡/协同效应——以张掖市为例	姚礼堂，张学斌，周亮，罗君，王梓洋，雷越，李意霞
2021	MOUNTAIN RESEARCH	Discussion on compensation mode of "blood production" in mountain area based on ecological compensation analysis -- taking north section	于淑会 1a，1b，3，闫秋宇 1a，1b，邓伟 2，

		of Taihang Mountain as an example 基于生态补偿分析的山区"造血式"补偿模式探讨———以太行山河北段为例	3*，邢宇华 1a，1b，康园园 1a，1b
2010	Research of Soil and Water Conversation	Environmental impact assessment of land use planning in Guyuan City based on ecosystem service value 基于生态系统服务价值的固原市市辖区土地利用规划环境影响评价	王亚娟, 刘小鹏, 赵大磊
2011	Journal of Natural Resource	Effects of Conversion of farmland to Forest project on ecosystem service value in low hilly area of Sichuan Basin: A case study of Hongya County 退耕还林工程对四川盆周低山丘陵区生态系统服务价值的影响——以洪雅县为例	赖元长, 李贤伟, 冯帅, 王鹏, 唐骄萍, 赵安玖,赖家明
2013	Journal of Arid Land Resources and Environment 干旱区资源与环境	Response of Ecological service Value to Landscape pattern Evolution in Qinling Mountains -- A Case Study of Shangluo City 秦岭山区景观格局演变的生态服务价值响应研究*———以商洛市为例	刘焱序 1，任志远 1，2，李春越 2

2013	Science and technology management of land and resources 国土资源科技管理	Effects of land use change on ecosystem service value in hilly and mountainous areas of southwest China 西南丘陵山区土地利用变化对生态系统服务价值的影响	程　飞 1，杨朝现 1，2，梁永莉 3，侯俊国 1，付　凯 1，邵丽亚
2014	Journal of Guizhou Normal University (Natural Science Edition 贵州师范大学学报(自然科学版	Response of ecological service value to conversion of farmland to forest (grassland) project in Karst mountainous area 岩溶山区生态服务价值对退耕还林(草)工程的响应	郜红娟 1，张朝琼 2*，王后阵 2
2015	Journal of Southwest Agricultural Sciences	Spatial coupling and ecological effects of land use/cover change in Kashgar River Basin, Xinjiang, 1990-2018 1990—2018 年新疆喀什噶尔河流域土地利用/覆被变化空间耦合及其生态效应	
2016	Journal of Nanjing Forestry University (Natural Science Edition)	Changes of ecosystem service values along highways in Mountainous areas of Guizhou province 贵州山区公路沿线生态系统服务价值变化	郜红娟 1，罗绪强 1 *，韩会庆 1，王后阵 2

2016	MOUNTAIN RESEARCH	Effects of returning cropland to forest on the change of ecological service value in alpine settlements in the upper reaches of Minjiang River 退耕还林对岷江上游高山聚落区生态服务价值变化的影响	樊敏，李富程，郭亚琳，王青
2016	Research of Soil and Water Conversation	Ecological service value of land around Beijing and Tianjin based on zoning and grey prediction 基于分区的环京津土地生态服务价值及灰色预测	李恒哲 1，李超 3，陈召亚 1，郭年冬 1，许皞 1， 2，王树涛 2
2016	Chinese Journal of Eco-Agriculture	The study of the influence of climate change and human activity on the value of the service value of human activity 焉耆盆地气候变化和人类活动对生态系统服务价值的影响研究	哈丽旦·司地克 玉素甫江·如素力** 麦麦提吐尔逊·艾则孜
2017	Jiangsu Agricultural Sciences 江苏农业科学	Study on the relationship between urban land use change and ESV in Karst mountainous areas: A case study of Guiyang, Guizhou Province 喀斯特山区都市土地利用变	余晓芳 1，2，安裕伦 1，2，安宁 3，姜海峰 1

		化与 ESV 关系研究———以贵州省贵阳市为例	
2018	Research of Soil and Water Conversation	Assessment of ecosystem services value of the Intermountain Basin in northwestern Hebei Province based on topographic gradient: A case study of Huailai County, Hebei Province 基于地形梯度的冀西北间山盆地生态系统服务价值评估———以河北省怀来县为例	
2018	Research of Soil and Water Conversation	Influence of land use change on ecological service value in Western Henan mountainous area 豫西山区土地利用变化对生态服务价值的影响	陈万旭，李江风，姜卫，朱丽君，熊锦惠
2019	MA Environmental Science and Geography 地理、环境科学	Study on Land Use Change and Ecological Service Value in Wumeng Mountain Area -- A Case Study of Hezhang County, Guizhou Province 乌蒙山区土地利用变化及生态服务价值研究*———以贵州省赫章县为例	徐志荣，赵翠薇
2019	Environ Sci Tech 环境科学与技术	Evaluation of ecosystem service value in karst mountainous area based on LUCC	唐启琳 1,2，刘方 1，刘

		基于 LUCC 的喀斯特山区生态系统服务价值评价	秀明 2*，汪花 1,
2019	Ecological Science	Study on the evolution of farmland landscape pattern and its ecological service function in Fujian Triangle region 闽三角地区农田景观格局演变及其生态服务功能研究	林金煌 1, 吴思佳 1, 陈文惠 1*, 王智蕊 2, 程瑞彤 1, 陈增文 3, 余锦慧 1
2019	Acta Ecologica Sinica	Spatial-temporal evolution of ecological land use and its response to ecosystem services in Luoxiao Mountain: A case study of Jinggang Mountain 罗霄山区生态用地时空演变及其生态系统服务功能的响应———以井冈山为例	璩路路 1，刘彦随 1，2，3，*，周扬 2，3，李裕瑞 2，3
2019	Research of Soil and Water Conversation	Effects of land use transformation process on ecosystem service value in karst trough valley region 喀斯特槽谷区土地利用转型过程对生态系统服务价值的影响	王权，李阳兵，黄娟，胡先培，钟盛楠
2019	Research of Soil and Water Conversation	Gains and losses of ecosystem services value in Qihe River Basin based on topographic gradient characteristics	

		基于地形梯度特征淇河流域生态系统服务价值损益	
2020	Study Methodology of Environmental Science 环境科学研究	Spatial-temporal changes of ecosystem service value at township scale in Dalou Mountain area 乡镇尺度大娄山区生态系统服务价值时空变化研究	姜栋栋 1，3，马伟波 2*，邹凤丽 2，4，李海东 2，张龙江 2，刘桂建 1
2020	Acta Ecologica Sinica	Positive and negative value of ecosystem services based on mountain - oasis - desert system -- A Case study of Manas River Basin in Xinjiang Province 基于山地-绿洲-荒漠系统的生态系统服务正负价值测算———以新疆玛纳斯河流域为例	夏鑫鑫 1，2，朱磊 1，2，*，杨爱民 1，2，靳含 1，2，张青青 1，
2020	Subtropical Soil and Water Conservation	Changes of land use and ecosystem service value in typical mountainous areas: A case study of Mentougou District, Beijing 典型山区土地利用及生态系统服务价值变化——以北京市门头沟区为例	
2021	Journal of Fujian Normal University (Natural Science	The influence of land use pattern change on ecological service value in mountainous	杜亚运 1，2，戴文远 1，2，3，武

	Edition 福建师范大学学报(自然科学版	areas: A case study of Shaxian County, Fujian Province 山区县域土地利用格局变化对生态服务价值的影响———以福建省沙县为例	国胜 1，2，3，林涛 1，2
2021	Hubei Agricultural Sciences 湖北农业科学	Spatial-temporal evolution of ecosystem service value in Minshan Area of Giant Panda National Park 大熊猫国家公园岷山片区生态系统服务价值的时空演变	汪琳，付潇，朱创业
2021	Hunan Agricultural Sciences 湖南农业科学	Spatial-temporal evolution of ecosystem service value in Wuling Mountain area of Hunan Province 湖南省武陵山片区生态系统服务价值时空演变研究	王盈丽，庄大春，董贤斌，樊简，邹妤阳
2021	Study Methodology of Environmental Science 环境科学研究	Change and scenario prediction of ecosystem service value in Dalou Mountain area 大娄山区生态系统服务价值变化与情景预测	姜栋栋，杨帆，马伟波，李海东，张龙江，刘桂建
2021	Journal of Agricultural Resources and Environmen	The evolution of ecological land and the response of ecological service value in the county of low hill area 低山丘陵区县域生态用地演变及生态服务价值响应	邢晓露，郭岚*，杨梅焕，张全文，王益展

2021	Acta Ecologica Sinica	Spatial response of ecosystem service value to urbanization based on terrain gradient in southern hilly and mountainous belt: A case study of northern Guangdong province 基于地形梯度的南方丘陵山地带生态系统服务价值对城市化的空间响应———以粤北地区为例	石宇，韩蕊，郭泺*
2022	Journal of Environmental Engineering Technology 环境工程技术学报	Effects of land use change on ecosystem service value in karst mountainous area 喀斯特山区土地利用变化对生态系统服务价值的影响	李文芳，任晓冬*，刘弋菱，王霄念，肖杰
2017	Journal of Nanjing Forestry University (Natural Sciences edition)	Temporal and spatial changes of garden and its impact on ecological service value in mountain cities 山地城市园地时空变化及对生态服务价值的影响	韩会庆 1，罗绪强 1 *，蔡广鹏
2010	ECOLOGICAL ENVIRONMENT	Impact of land use change on ecosystem service value in mountainous areas: A case study of Pengyang County, Ningxia 山区土地利用变化对生态系统服务价值的影响分析——以宁夏彭阳县为例	王亚娟 1, 2 刘小鹏 1 关文超 1

2020	Acta Ecologica Sinica	Impacts of land use change on ecosystem services and human welfare in villages with different tourism patterns in Hani Terraced Fields 哈尼梯田区不同旅游模式村寨土地利用变化对生态系统服务与人类福利的影响	张娟，陈凡，角媛梅*，刘澄静，赵冬梅，刘志林，徐秋娥，邱应美
2013	Progress in geography 地理科学进展	Ecosystem service zoning in Beijing-Tianjin-Hebei region based on SOFM network 基于 SOFM 网络的京津冀地区生态系统服务分区	马程 1，李双成 1，刘金龙 1,2，高阳 1，王阳
2013	Regional Research and development 地域研究与开发	Estimation of potential impact of land development and consolidation on regional environment: A case study of Hebei Province 土地开发整理对区域环境潜在影响估算———以河北省为例	刘浩杰 1a，1b，刘宏娟 1a，1b，元媛 2，刘慧涛 1a，1b，谭莉梅 1a，1b，刘金铜
2019	Acta Agriculturae Jiangxi	Land use change and its impact on ecosystem service value in Wumeng Mountain 乌蒙山区土地利用变化及其对生态系统服务价值的影响	唐孝甲 1，唐学君 1，2*，张伟东 1
2021	Journal of Dalian Minzu University 大连民族大学学报	Evaluation of tourism island ecosystem service value based on LUCC: A case study of Dachangshan Island 基于 LUCC 的旅游型海岛生	王辉，彭霞

		态系统服务价值评估———以大长山岛为例	
2013	Chinese Journal of Ecology	Effects of land use change on ecosystem services in the Loess Plateau: A case study of Ningwu County 黄土高原土石山区土地利用变化对生态系统服务的影响———以宁武县为例	刘秀丽 1，2 张勃 2＊＊ 张调风 2 何旭强
2020	Science Technology and Engineering 科学技术与工程	Responses of land use change and ecosystem service value in mountainous county: A case study of Songxian County 山区县域土地利用变化及其生态系统服务价值响应———以嵩县为例	尹泽凯 1，谭立峰 2，贾琦 3
2020	Research of Soil and Water Conversation	The gradient characteristics of ecosystem service value change in mountain cities under the background of rapid urbanization: A case study of Guiyang City 快速城镇化背景下山地城市生态系统服务价值变化梯度特征———以贵阳市为例	韩会庆 1，刘悦 1，蔡广鹏 2，白玉梅 1，马淑亮 1，陈思盈 1，罗瑞尧 1
2021	Chinese Journal of Ecology	Ecosystem service value of mine park in the context of ecological restoration: A case study of Purple Mountain in Fujian Province	罗琳，杨璐，谢红

		生态修复背景下矿山公园生态系统服务价值——以福建紫金山为例	彬，关钊，魏平
2022	Research of Soil and Water Conversation	Evolution of ecosystem service value in Kunyu Mountain National Nature Reserve 昆嵛山国家级自然保护区生态系统服务价值演变	张文馨 1，范小莉 1，王强 2，房用 1，时良 3，梁玉
2021	Acta Ecologica Sinica	A study on the selection of priority protected areas based on ecosystem service tradeoffs: A case study of hilly and montane zones in southern China 基于生态系统服务权衡的优先保护区选取研究———以南方丘陵山地带为例	王良杰 1，2，*，马帅 1，2，许稼昌 1，2，朱殿珍 1，2，张金池 1，2
2021	Research of Soil and Water Conversation	Topographic gradient response of urban ecosystem service value in karst mountainous areas: A case study of Guiyang City 喀斯特山地城市生态系统服务价值地形梯度响应——以贵阳市中心城区为例	
2019	Acta Ecologica Sinica	Study on the impact of land use change on ecological service value in Funiu Mountain based on grid 基于格网的伏牛山区土地利	郭椿阳 1，高尚 2，周

		用变化对生态服务价值影响研究	伯燕 1，高建华 1，*
2013	Environmental protection science 环境保护科学	Study on ecosystem service function improvement of land restoration in coal mine area 煤矿区土地修复的生态系统服务功能改善研究	董方圆，李国旗，王磊，蒋齐
2018	Acta Ecologica Sinica	Tradeoff optimization of ecosystem services in Jiajiyu watershed based on multi-objective linear programming 基于多目标线性规划的甲积峪小流域生态系统服务权衡优化	包蕊 1，刘峰 1，*，张建平 2，段颖琳 1，赵帅 1，严晓亚 3，刘英 4
2014	Research of Soil and Water Conversation	Analysis of ecological service Value of coal mining subsidence land in Southwest mountainous area -- Taking Songzao Mining area of Chongqing City as an example 西南山区采煤塌陷地生态服务价值分析———以重庆市松藻矿区为例	唐紫晗 1，2，李妍均 1，2，陈朝 1，3，鲁嘉濠 1
2020	Acta Ecologica Sinica	Coupling coordination degree between ecosystem services and landscape pattern: A case study of Conversion of farmland to forest in Wuling Mountain Area 生态系统服务功能与景观格	李慧杰 1，2，3，4，牛香 2，3，4，王兵 1，2，

		局耦合协调度研究———以武陵山区退耕还林工程为例	3， 4，*，赵志江 5
2019	Chinese Journal of Ecology	Spatial patterns of ecosystem services and their tradeoffs and synergies in the Loess hilly region: A case study of Yuzhong County 黄土丘陵区生态系统服务空间格局及权衡与协同关系———以榆中县为例	王川 1，2 刘春芳 1，2* 乌亚汗 1，2 刘宥延 1，2
2021	Acta Ecologica Sinica	Ecological security pattern construction in Karst mountainous area based on ecosystem service importance and environmental sensitivity: A case study of Hechi, Guangxi 基于生态系统服务重要性和环境敏感性的喀斯特山区生态安全格局构建———以广西河池为例	高梦雯 1，胡业翠 1，2，*，李向 1，宋荣
2021	Acta Ecologica Sinica	Evaluation of key ecological space in the North Slope Economic zone of Tianshan Mountains 天山北坡经济带关键性生态空间评价	田浩，刘琳 *，张正勇，赵贵宁，宁珊，康紫薇，王统霞
2008	RESOURCES SCIENCE	Analysis of land use and ecosystem function change in different landscape areas on the Northern Slope of	吴建寨,李波,崇洁,张新时

		Tianshan Mountain 天山北坡不同景观区域土地利用与生态系统功能变化分析	
2018	Research of Soil and Water Conversation	Spatial and temporal changes of ecosystem service value in the middle reaches of the Yangtze River Economic Belt from 1990 to 2014 1990-2014 年长江中游经济带生态系统服务价值时空变化特征	

6.2 Appendix B

Supplementary material: Chapter 2

6.2.1 Temporal Trend Visualization of ES and LULC

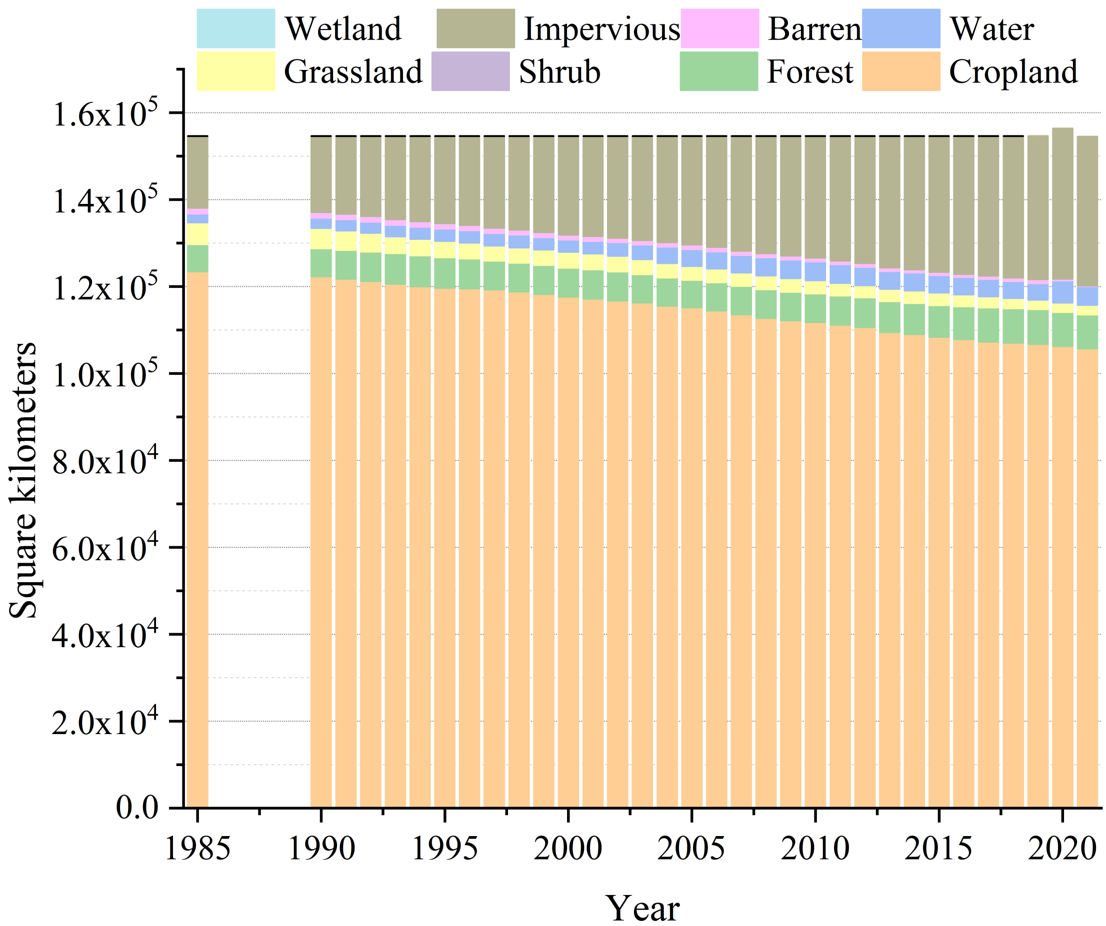


Figure Land use change trend.

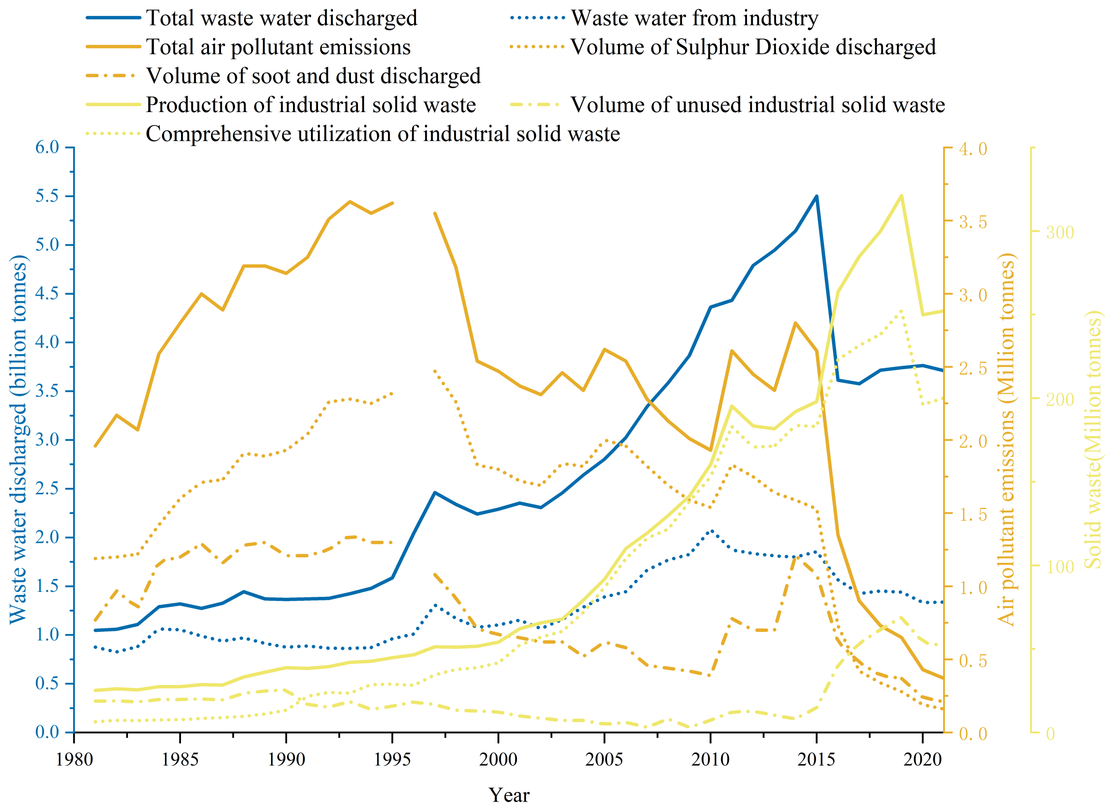


Figure 6.2-1 Wastewater discharge, air pollution emission and solid waste.

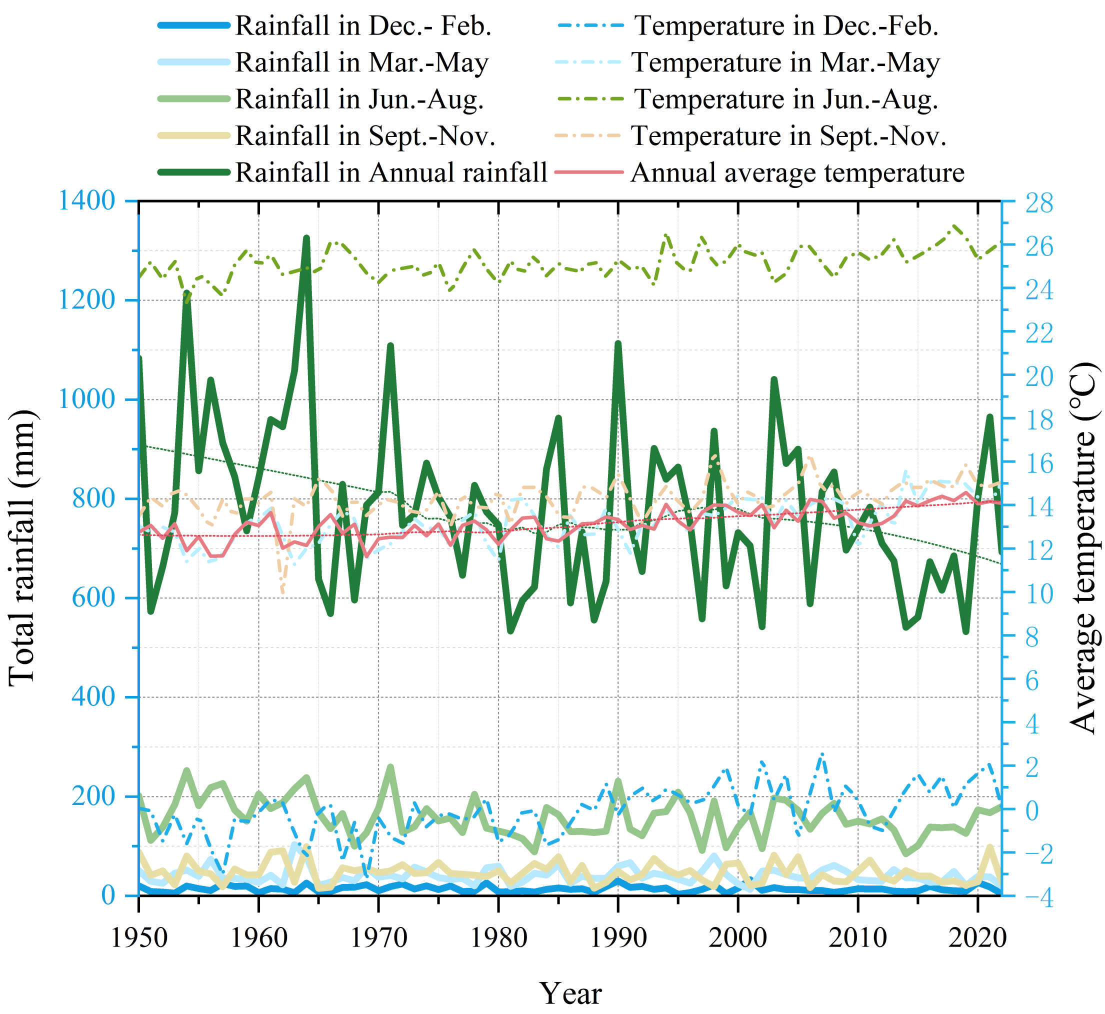


Figure 6.2-2 Seasonal and annual rainfall and temperature changes.

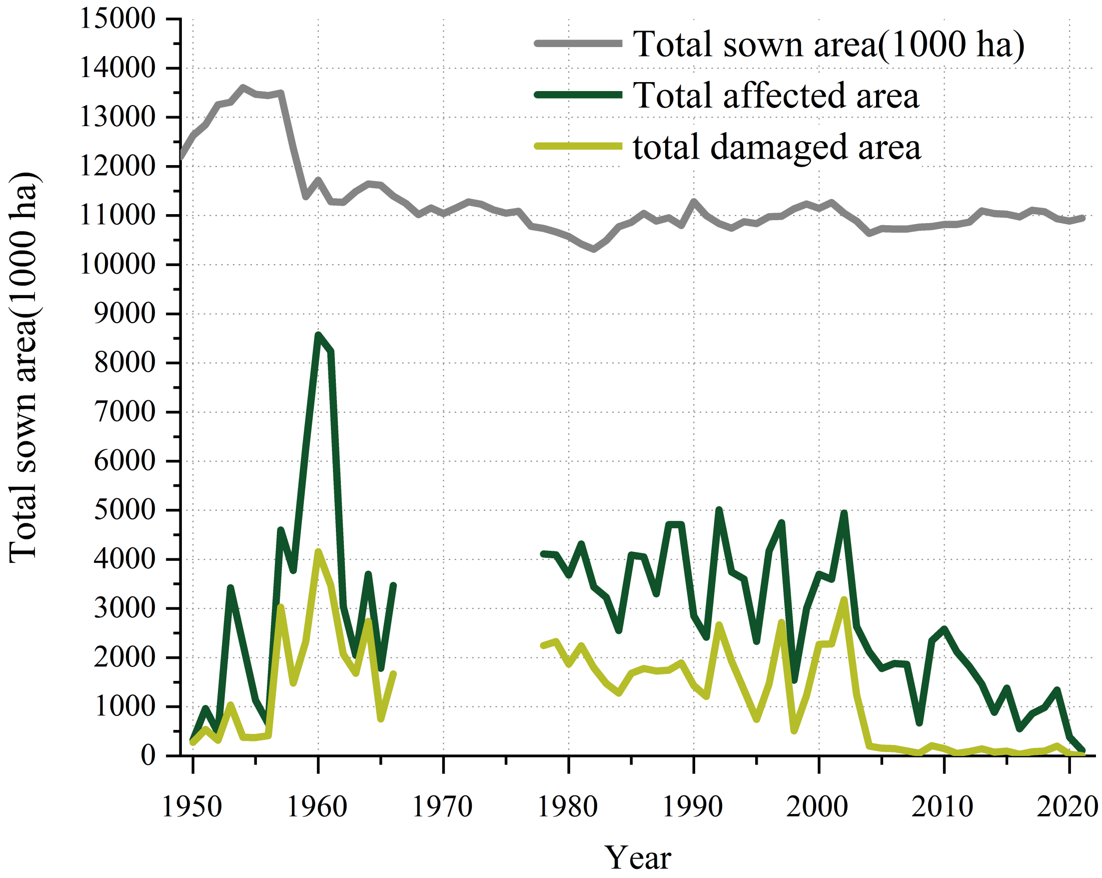


Figure 6.2-3 Hazard affected sown area and damaged sown area.

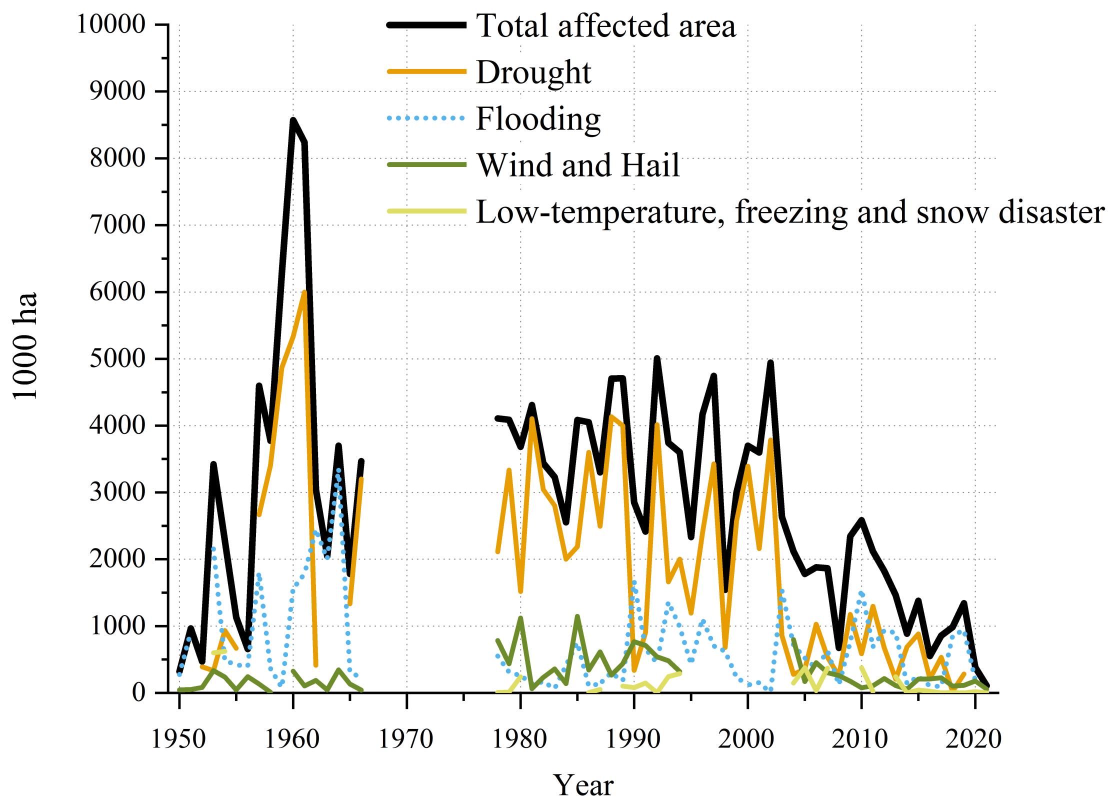


Figure 6.2-4 Different hazards affected area.

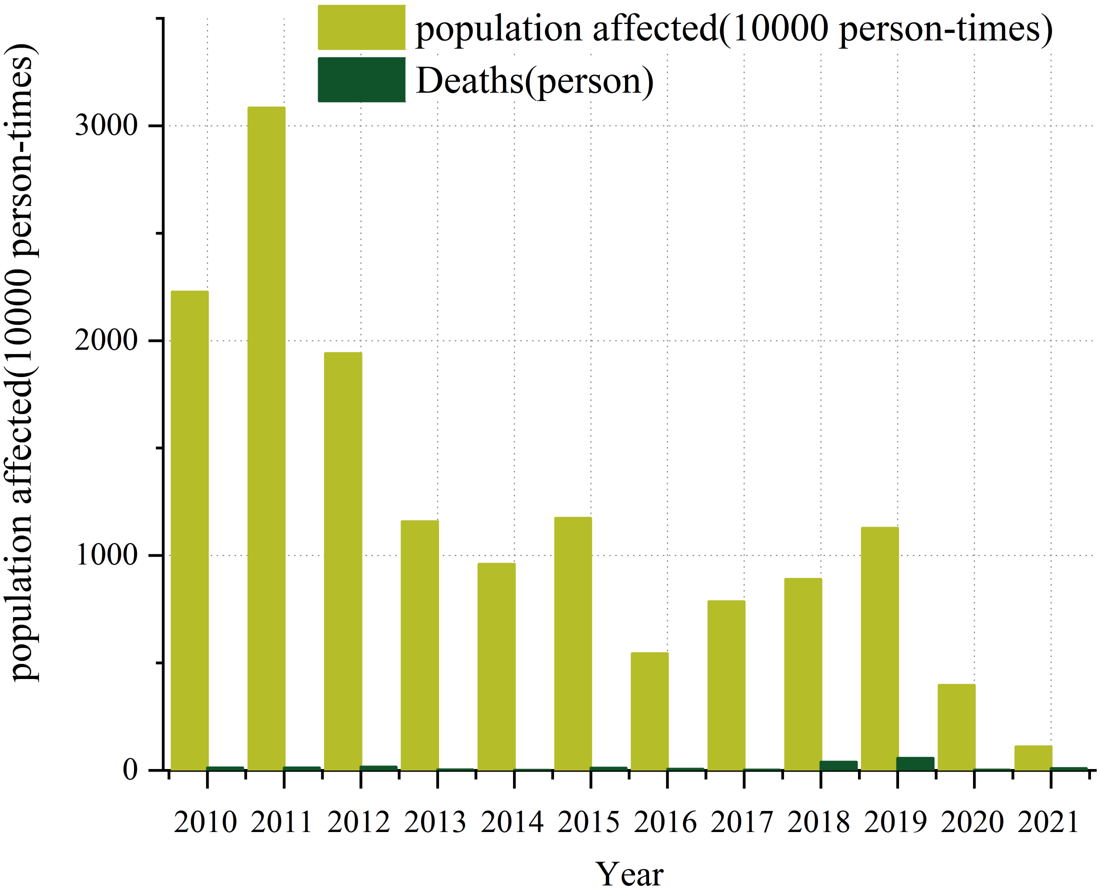


Figure 6.2-5 Hazards affected population.

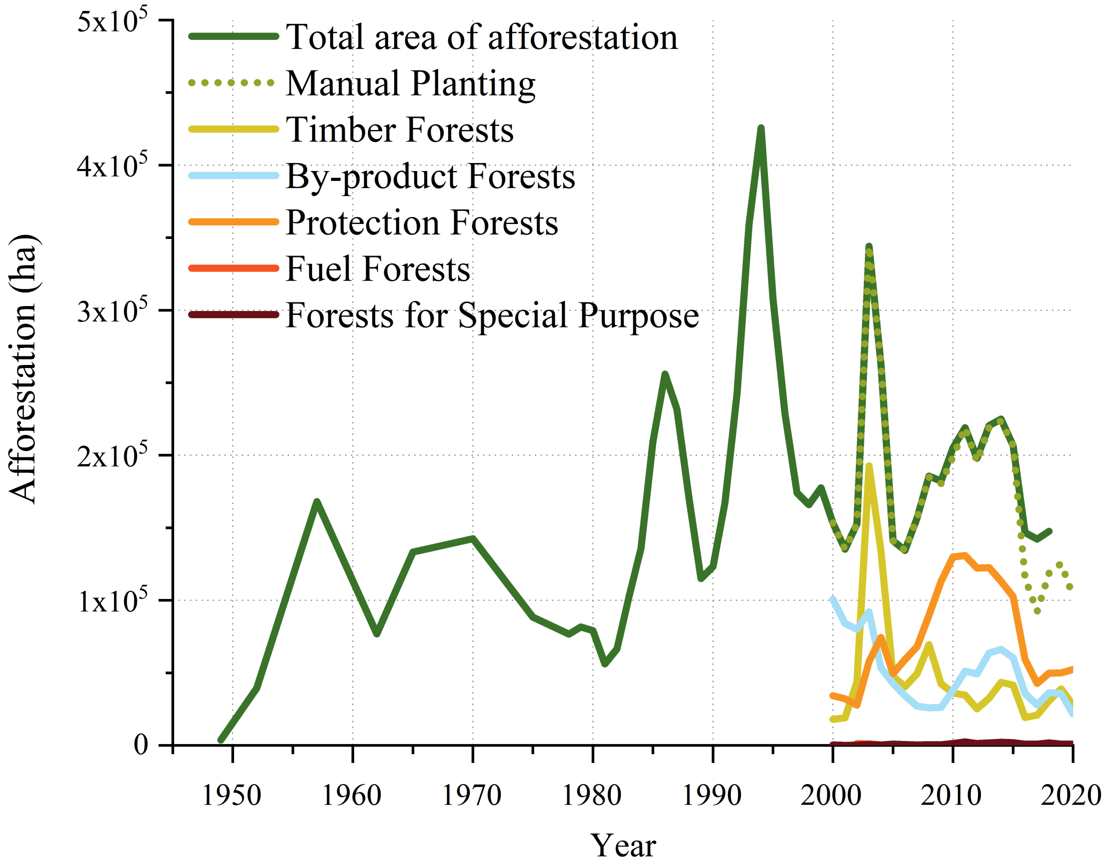


Figure 6.2-6 Afforestation and forest usage.

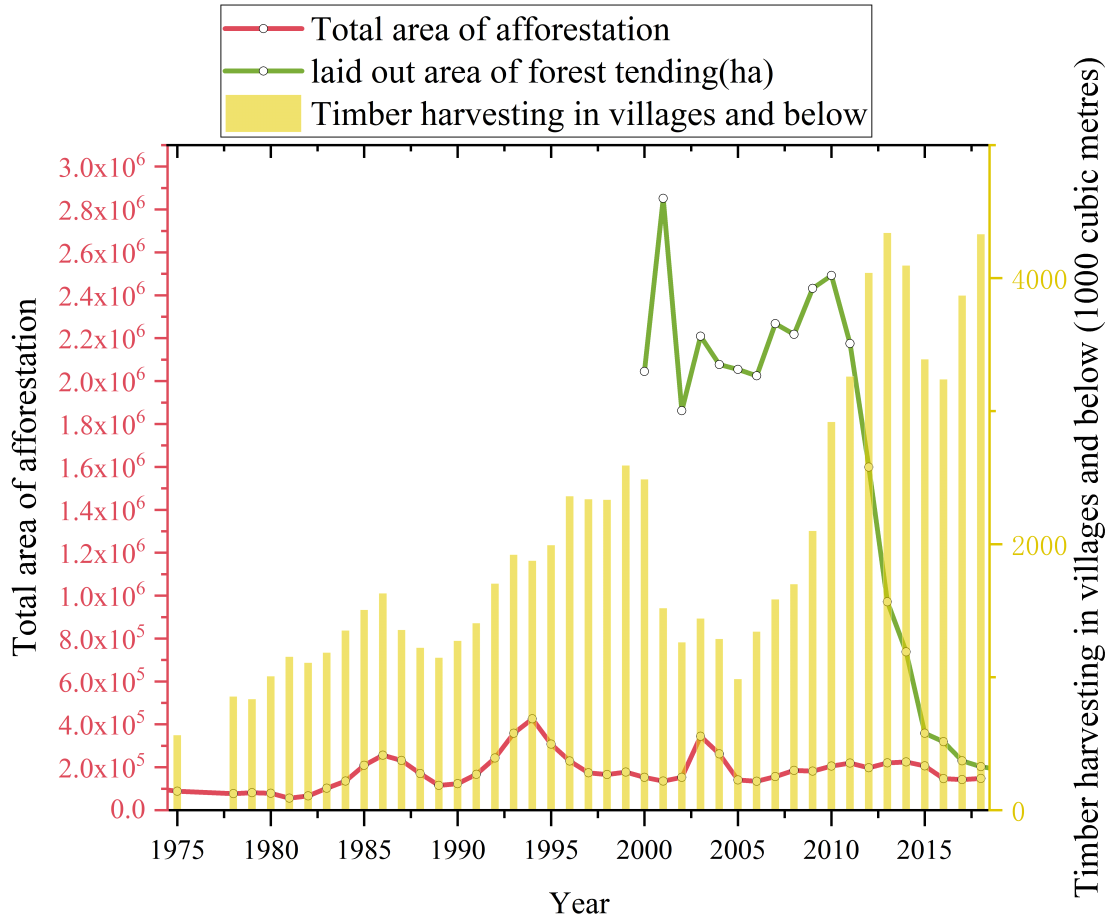


Figure 6.2-7 Afforestation and timber production.

6.2.2 SPCA and Early Warning Signals (EWS)

To detect structural evolution, potential regime shifts, and resilience changes in ES, this study employed sPCA approach. These methods were applied to three subsystems: (1) internal ES dynamics, (2) ES-LULC coupling, and (3) ES-GDP interactions. This combined approach has proven effective for diagnosing instability and reorganization in complex social-ecological systems (Scheffer et al., 2009; Dakos et al., 2012).

6.2.2.1 Method Overview

This section outlines the integrated approach of SPCA employed in this study to identify structural changes and potential tipping dynamics in the ES system. The method consists of three main steps:

(1) Rolling SPCA Analysis

SPCA uses a moving-window strategy to calculate the cumulative variance explained by the first three principal components (PC1, PC1 + PC2, and PC1 + PC2 + PC3). These components reflect the degree of structural coherence and coordination among system variables over time. This dynamic approach captures the evolving patterns of system organization.

(2) Change Point Detection

Structural change points are identified based on the rolling slope of the principal component trends. These change points are marked with red dashed lines in the trend plots, indicating moments when the system shifts from one dominant structural regime to another.

(3) Early Warning Signal (EWS) Indicators

To detect early signs of declining system resilience or impending instability, three standard indicators from the EWS framework are applied:

AR(1) (Autocorrelation at lag-1): Measures the correlation between consecutive observations. An increasing AR(1) trend indicates rising memory in the system, which is a typical signal of critical slowing down—a precursor to potential regime shifts.

SD (Standard Deviation): Reflects the overall variability of the system. A rising SD suggests increasing fluctuations, which may indicate weakening resilience and higher volatility.

Skew (Skewness): Measures the asymmetry in the distribution of system states. Increases in skewness imply a higher frequency of extreme states, potentially reflecting structural shifts or the emergence of a new system regime.

These indicators are calculated using the same moving-window approach as SPCA and are plotted over time to assess whether the ES system shows signs of approaching instability or undergoing structural reorganization.

6.2.2.1.1 Code of SPCA analysis and EWS between provisioning services and regulating services

```
# ===================== Step 1: Load Libraries and Data
=====================

library(zoo)

library(ggplot2)

library(Kendall)

library(EWSmethods)



data <- read.csv("ES.csv")  # Replace with your filename

time_column <- "Year"



# Interpolate missing values (excluding time column)

data_interp <- data

for (col in names(data)[-which(names(data) == time_column)]) {
```

```
  data_interp[[col]] <- na.spline(data[[col]])
}


# ===================== Step 2: SPCA (Sequential PCA: PC1, PC1+2,
PC1+2+3) =====================
window_size <- 20
num_windows <- nrow(data_interp) - window_size + 1


variance_pc1 <- numeric(num_windows)
variance_pc2 <- numeric(num_windows)
variance_pc3 <- numeric(num_windows)


for (i in 1:num_windows) {
  window_data <- data_interp[i:(i + window_size - 1), ]
  pca_result <- prcomp(window_data[, -which(names(window_data) ==
time_column)], scale. = TRUE)
  total_var <- sum(pca_result$sdev^2)
  variance_pc1[i] <- pca_result$sdev[1]^2 / total_var
  variance_pc2[i] <- sum(pca_result$sdev[1:2]^2) / total_var
```

```
  variance_pc3[i] <- sum(pca_result$sdev[1:3]^2) / total_var

}



# Mid-year of each rolling window

center_years <- data_interp$Year[(window_size:nrow(data_interp)) -
floor(window_size / 2)]

result_data <- data.frame(

  Year = center_years,

  PC1 = variance_pc1,

  PC2 = variance_pc2,

  PC3 = variance_pc3

)



# ====================== Step 3: Change Point Detection via Rolling Slope
(on PC1+PC2) ======================

roll_slope <- zoo::rollapply(result_data$PC2, width = 5,

                             FUN = function(x) coef(lm(x ~ seq_along(x)))[2],

                             fill = NA, align = "right")
```

```
threshold <- quantile(roll_slope, 0.1, na.rm = TRUE)

change_years <- result_data$Year[which(roll_slope < threshold)]



# ====================== Step 4: Mann-Kendall Trend Test (on PC1+PC2)
======================

mk_test <- MannKendall(result_data$PC2)

mk_p_value <- mk_test$sl



# ====================== Step 5: Early Warning Signals
(EWSmethods::uniEWS) ======================

ews_input <- data.frame(

  time = result_data$Year,

  abundance = result_data$PC2

)



ews_result <- uniEWS(

  data = ews_input,

  metrics = c("SD", "ar1", "skew"),  # Optional: kurt, cv

  method = "rolling",
```

```
  winsize = 20
)


# Print Kendall tau values for EWS metrics
print(ews_result$EWS$cor)


# ====================== Step 6: Plot SPCA Trend and Change Points
======================
ggplot(result_data, aes(x = Year)) +
  geom_line(aes(y = PC1, color = "PC1"), size = 1) +
  geom_line(aes(y = PC2, color = "PC1+PC2"), size = 1) +
  geom_line(aes(y = PC3, color = "PC1+PC2+PC3"), size = 1) +
  geom_vline(xintercept = change_years, linetype = "dashed", color = "red") +
  labs(title = "SPCA Trend of Ecosystem Service Variables",
       subtitle = paste("Mann-Kendall p-value (PC1+PC2):", round(mk_p_value, 4)),
       x = "Year", y = "Proportion of Variance", color = "Principal Component") +
  scale_color_manual(values = c("PC1" = "red", "PC1+PC2" = "green",
"PC1+PC2+PC3" = "blue")) +
  theme_minimal(base_size = 14)
```

```
# Save plot

ggsave("SPCA_ES_trend_with_change.tiff", width = 10, height = 6, dpi = 300)

# ====================== Step 7: Visualize EWS Metrics
======================

plot(ews_result)

# ====================== Step 8: Export SPCA Trend and Change Points
======================

write.csv(result_data, "SPCA_ES_Proportion_Trends.csv", row.names = FALSE)

write.csv(data.frame(Change_Year = change_years),
"SPCA_ES_Change_Points.csv", row.names = FALSE)

# ====================== Step 9: Export Full-Sample PCA Loadings
======================

pca_full <- prcomp(data_interp[, -which(names(data_interp) == time_column)], scale.
= TRUE)

variances <- pca_full$sdev^2

loadings <- pca_full$rotation
```

```
proportion_of_variance <- variances / sum(variances)

cumulative_proportion <- cumsum(proportion_of_variance)



result_loadings <- data.frame(

  Principal_Component = 1:length(variances),

  Variance = variances,

  Proportion_of_Variance = proportion_of_variance,

  Cumulative_Proportion = cumulative_proportion

)



# Add variable-wise loadings

for (i in 1:ncol(loadings)) {

  result_loadings[[paste0("Loading_PC", i)]] <- loadings[, i]

}

result_loadings$Variable <- rownames(loadings)



# Save to CSV

write.csv(result_loadings, "SPCA_result_loadings_ES.csv", row.names = FALSE)
```

6.2.2.1.2 Code of SPCA analysis and EWS between ESs and LULC

```
# ====================== Step 1: Load Libraries and Data
======================

library(zoo)

library(ggplot2)

library(Kendall)

library(EWSmethods)



data <- read.csv("ES@.csv")  # ← Replace with your filename

time_column <- "Year"



# Interpolate missing values (excluding Year)

data_interp <- data

for (col in names(data)[-which(names(data) == time_column)]) {

  data_interp[[col]] <- na.spline(data[[col]])

}



# ====================== Step 2: SPCA (PC1, PC1+2, PC1+2+3)
======================
```

```
window_size <- 20

num_windows <- nrow(data_interp) - window_size + 1



variance_pc1 <- numeric(num_windows)

variance_pc2 <- numeric(num_windows)

variance_pc3 <- numeric(num_windows)



for (i in 1:num_windows) {

  window_data <- data_interp[i:(i + window_size - 1), ]

  pca_result <- prcomp(window_data[, -which(names(window_data) ==
time_column)], scale. = TRUE)

  total_var <- sum(pca_result$sdev^2)

  variance_pc1[i] <- pca_result$sdev[1]^2 / total_var

  variance_pc2[i] <- sum(pca_result$sdev[1:2]^2) / total_var

  variance_pc3[i] <- sum(pca_result$sdev[1:3]^2) / total_var

}



# Mid-year of each window
```

```
center_years <- data_interp$Year[(window_size:nrow(data_interp)) -
floor(window_size / 2)]

result_data <- data.frame(

  Year = center_years,

  PC1 = variance_pc1,

  PC2 = variance_pc2,

  PC3 = variance_pc3

)



# ====================== Step 3: Change Point Detection (Rolling Slope)
======================

roll_slope <- zoo::rollapply(result_data$PC2, width = 5,

                             FUN = function(x) coef(lm(x ~ seq_along(x)))[2],

                             fill = NA, align = "right")



threshold <- quantile(roll_slope, 0.1, na.rm = TRUE)

change_years <- result_data$Year[which(roll_slope < threshold)]



# ====================== Step 4: Mann-Kendall Trend Test
======================
```

```
mk_test <- MannKendall(result_data$PC2)

mk_p_value <- mk_test$sl


# ====================== Step 5: Early Warning Signals (EWSmethods)
======================

ews_input <- data.frame(

  time = result_data$Year,

  abundance = result_data$PC2

)


ews_result <- uniEWS(

  data = ews_input,

  metrics = c("SD", "ar1", "skew"),  # Optional: add kurt, cv

  method = "rolling",

  winsize = 20

)


# Print Kendall tau values for EWS metrics

print(ews_result$EWS$cor)
```

```
# ====================== Step 6: Plot SPCA Trend
======================

ggplot(result_data, aes(x = Year)) +

  geom_line(aes(y = PC1, color = "PC1"), size = 1) +

  geom_line(aes(y = PC2, color = "PC1+PC2"), size = 1) +

  geom_line(aes(y = PC3, color = "PC1+PC2+PC3"), size = 1) +

  geom_vline(xintercept = change_years, linetype = "dashed", color = "red") +

  labs(title = "SPCA Trend of ES + LULC Variables",

       subtitle = paste("Mann-Kendall p-value (PC1+PC2):", round(mk_p_value, 4)),

       x = "Year", y = "Proportion of Variance", color = "Principal Component") +

  scale_color_manual(values = c("PC1" = "red", "PC1+PC2" = "green",
"PC1+PC2+PC3" = "blue")) +

  theme_minimal(base_size = 14)



# Save plot

ggsave("SPCA_ES_LULC_trend_with_change.tiff", width = 10, height = 6, dpi =
300)
```

```
# ====================== Step 7: Visualize EWS Metrics
======================

plot(ews_result)



# ====================== Step 8: Export Trend & Change Point
======================

write.csv(result_data, "SPCA_ES_LULC_Proportion_Trends.csv", row.names =
FALSE)

write.csv(data.frame(Change_Year = change_years),
"SPCA_ES_LULC_Change_Points.csv", row.names = FALSE)



# ====================== Step 9: Export PCA Loadings (Full Sample)
======================

pca_full <- prcomp(data_interp[, -which(names(data_interp) == time_column)], scale.
= TRUE)

variances <- pca_full$sdev^2

loadings <- pca_full$rotation

abs_loadings <- abs(loadings)



proportion_of_variance <- variances / sum(variances)

cumulative_proportion <- cumsum(proportion_of_variance)
```

```
result_loadings <- data.frame(
  Principal_Component = 1:length(variances),
  Variance = variances,
  Proportion_of_Variance = proportion_of_variance,
  Cumulative_Proportion = cumulative_proportion
)

# Add loadings per variable
for (i in 1:ncol(loadings)) {
  result_loadings[[paste0("Loading_PC", i)]] <- loadings[, i]
}
result_loadings$Variable <- rownames(loadings)

# Save loadings
write.csv(result_loadings, "SPCA_result_loadings_ES_LULC.csv", row.names =
FALSE)
```

6.2.2.1.3 Code of SPCA analysis and EWS about all ESs and GDP and population

```
# ====================== Step 1: Load Data and Apply Interpolation
======================

library(zoo)

library(ggplot2)

library(Kendall)

library(EWSmethods)



data <- read.csv("ES-.csv")  # ← Replace with your filename

time_column <- "Year"



# Apply spline interpolation to missing values (excluding the time column)

data_interp <- data

for (col in names(data)[-which(names(data) == time_column)]) {

  data_interp[[col]] <- na.spline(data[[col]])

}
```

```
# ===================== Step 2: SPCA - Proportion of Variance Explained
=====================

window_size <- 20

num_windows <- nrow(data_interp) - window_size + 1



variance_pc1 <- numeric(num_windows)

variance_pc2 <- numeric(num_windows)

variance_pc3 <- numeric(num_windows)



for (i in 1:num_windows) {

  window_data <- data_interp[i:(i + window_size - 1), ]

  pca_result <- prcomp(window_data[, -which(names(window_data) ==
time_column)], scale. = TRUE)

  total_var <- sum(pca_result$sdev^2)

  variance_pc1[i] <- pca_result$sdev[1]^2 / total_var

  variance_pc2[i] <- sum(pca_result$sdev[1:2]^2) / total_var

  variance_pc3[i] <- sum(pca_result$sdev[1:3]^2) / total_var

}
```

```
# Create results dataframe using the center year of each window

center_years <- data_interp$Year[(window_size:nrow(data_interp)) -
floor(window_size / 2)]

result_data <- data.frame(

  Year = center_years,

  PC1 = variance_pc1,

  PC2 = variance_pc2,

  PC3 = variance_pc3

)



# ==================== Step 3: Change Point Detection Using Rolling Slope
====================

roll_slope <- zoo::rollapply(result_data$PC2, width = 5,

                             FUN = function(x) coef(lm(x ~ seq_along(x)))[2],

                             fill = NA, align = "right")



threshold <- quantile(roll_slope, 0.1, na.rm = TRUE)  # Bottom 10% slope as
potential change points

change_years <- result_data$Year[which(roll_slope < threshold)]
```

```
# ====================== Step 4: Mann-Kendall Trend Test
======================

mk_test <- MannKendall(result_data$PC2)

mk_p_value <- mk_test$sl  # Significance level of trend (p < 0.05 indicates
significance)


# ====================== Step 5: Early Warning Signals
(EWSmethods::uniEWS) ======================

ews_input <- data.frame(

  time = result_data$Year,

  abundance = result_data$PC2

)


ews_result <- uniEWS(

  data = ews_input,

  metrics = c("SD", "ar1", "skew"),  # Optional: "kurt", "cv", etc.

  method = "rolling",

  winsize = 20

)
```

```
# Print Kendall tau values for EWS indicators

print(ews_result$EWS$cor)


# ====================== Step 6: Plot SPCA Trend and Change Points
======================

ggplot(result_data, aes(x = Year)) +

  geom_line(aes(y = PC1, color = "PC1"), size = 1) +

  geom_line(aes(y = PC2, color = "PC1+PC2"), size = 1) +

  geom_line(aes(y = PC3, color = "PC1+PC2+PC3"), size = 1) +

  geom_vline(xintercept = change_years, linetype = "dashed", color = "red") +

  labs(title = "SPCA Trend of ES + GDP Variables",

       subtitle = paste("Mann-Kendall p-value (PC1+PC2):", round(mk_p_value, 4)),

       x = "Year",

       y = "Proportion of Variance",

       color = "Principal Component") +

  scale_color_manual(values = c("PC1" = "red", "PC1+PC2" = "green",
"PC1+PC2+PC3" = "blue")) +

  theme_minimal(base_size = 14) +

  theme(
```

```
    plot.title = element_text(face = "bold", size = 16),
    legend.position = "top"
  )

# (Optional) Save the figure in high resolution
ggsave("SPCA_ES_GDP_trend_with_change.tiff", width = 10, height = 6, dpi = 300)

# ====================== Step 7: Visualize Early Warning Signals
======================
plot(ews_result)

# ====================== Step 8: Export SPCA Trend and Detected Change
Points ======================
write.csv(result_data, "SPCA_ES_GDP_Proportion_Trends.csv", row.names =
FALSE)
write.csv(data.frame(Change_Year = change_years),
"SPCA_ES_GDP_Change_Points.csv", row.names = FALSE)
```

6.2.3 EKC analysis

6.2.3.1 Method of EKC analysis

To evaluate whether environmental indicators follow the Environmental Kuznets Curve (EKC) hypothesis in the study region, this study conducted a series of quadratic regression analyses between per capita GDP and multiple ecosystem-related variables, including air pollution, wastewater discharge, forest cover, soil erosion, impervious surface, high-quality habitat, and low-quality habitat.

First, this study applied spline interpolation (zoo::na.spline) to fill missing values in the time series data to ensure continuity.

Second, scatter plots were generated to visually inspect potential nonlinear relationships between GDP and each environmental indicator.

Then, quadratic models of the form $y \sim GDP + GDP^2$ were fitted for each variable, and fitted curves were added to the plots to identify potential inverted-U or U-shaped patterns.

Finally, regression coefficients and p-values were extracted, and a faceted multi-panel EKC plot was created to summarize the economic–ecological response patterns across all indicators.

6.2.3.2 Code of EKC analysis in R

```
data <- read.csv("EKC.csv")

library(zoo)

# Interpolate missing values for each environmental indicator

forestcover_interp <- na.spline(data$forestcover)

print(forestcover_interp)
```

```
airpollution_interp <- na.spline(data$airpollution)

print(airpollution_interp)

Impervious_interp <- na.spline(data$Impervious)

print(Impervious_interp)

Wastewater_interp <- na.spline(data$Wastewater)

print(Wastewater_interp)

Low_interp <- na.spline(data$Low)

print(Low_interp)

Highhabitat_interp <- na.spline(data$Highhabitat)

print(Highhabitat_interp)

# Install and load necessary packages

install.packages("ggplot2")  # For plotting

install.packages("lmtest")   # For extended regression testing

library(ggplot2)

library(lmtest)

# Load dataset again (ensure the file is in the working directory)

data <- read.csv("EKC.csv")
```

```
# Draw scatter plots: GDP vs. Environmental Indicators

ggplot(data, aes(x = GDP, y = airpollution)) +

  geom_point() +

  labs(x = "GDP", y = "Air Pollution") +

  ggtitle("Scatter Plot of GDP vs. Air Pollution")



ggplot(data, aes(x = GDP, y = Wastewater)) +

  geom_point() +

  labs(x = "GDP", y = "Wastewater") +

  ggtitle("Scatter Plot of GDP vs. Wastewater")



ggplot(data, aes(x = GDP, y = forestcover)) +

  geom_point() +

  labs(x = "GDP", y = "Forest Cover") +

  ggtitle("Scatter Plot of GDP vs. Forest Cover")



ggplot(data, aes(x = GDP, y = soilerosion)) +

  geom_point() +
```

```
  labs(x = "GDP", y = "Soil Erosion") +
  ggtitle("Scatter Plot of GDP vs. Soil Erosion")


ggplot(data, aes(x = GDP, y = Impervious)) +
  geom_point() +
  labs(x = "GDP", y = "Impervious Land") +
  ggtitle("Scatter Plot of GDP vs. Impervious Land")


ggplot(data, aes(x = GDP, y = Highhabitat)) +
  geom_point() +
  labs(x = "GDP", y = "High Habitat") +
  ggtitle("Scatter Plot of GDP vs. High Habitat")


ggplot(data, aes(x = GDP, y = Low)) +
  geom_point() +
  labs(x = "GDP", y = "Low Habitat") +
  ggtitle("Scatter Plot of GDP vs. Low Habitat")
```

```
# Combine multiple plots into one canvas (optional)

library(gridExtra)


plot1_airpollution <- ggplot(data, aes(x = GDP, y = airpollution)) +

  geom_point() +

  labs(x = "GDP", y = "Air Pollution")


plot2_Wastewater <- ggplot(data, aes(x = GDP, y = Wastewater)) +

  geom_point() +

  labs(x = "GDP", y = "Wastewater")


plot3_forestcover <- ggplot(data, aes(x = GDP, y = forestcover)) +

  geom_point() +

  labs(x = "GDP", y = "Forest Cover")


plot4_soilerosion <- ggplot(data, aes(x = GDP, y = soilerosion)) +

  geom_point() +

  labs(x = "GDP", y = "Soil Erosion")
```

```
plot5_Impervious <- ggplot(data, aes(x = GDP, y = Impervious)) +
  geom_point() +
  labs(x = "GDP", y = "Impervious Land")

plot6_Highhabitat <- ggplot(data, aes(x = GDP, y = Highhabitat)) +
  geom_point() +
  labs(x = "GDP", y = "High Habitat")

plot7_Low <- ggplot(data, aes(x = GDP, y = Low)) +
  geom_point() +
  labs(x = "GDP", y = "Low Habitat")

# Arrange all plots together
grid.arrange(plot1_airpollution, plot2_Wastewater, plot3_forestcover,
             plot4_soilerosion, plot5_Impervious, plot6_Highhabitat, plot7_Low,
             ncol = 3)  # Adjust number of columns as needed
```

```
# Polynomial regression (quadratic) for each environmental indicator

# Example: air pollution

model1 <- lm(airpollution ~ GDP + I(GDP^2), data = data)

summary(model1)



ggplot(data, aes(x = GDP, y = airpollution)) +

  geom_point() +

  geom_smooth(method = "lm", formula = y ~ x + I(x^2), se = FALSE, color = "red")
+

  labs(x = "GDP", y = "Air Pollution") +

  ggtitle("Quadratic Regression: Air Pollution")



anova(model1)



# Repeat for other indicators

model2 <- lm(Wastewater ~ GDP + I(GDP^2), data = data)

summary(model2)

anova(model2)
```

```
model3 <- lm(forestcover ~ GDP + I(GDP^2), data = data)

summary(model3)

anova(model3)


model4 <- lm(soilerosion ~ GDP + I(GDP^2), data = data)

summary(model4)

anova(model4)


model5 <- lm(Impervious ~ GDP + I(GDP^2), data = data)

summary(model5)

anova(model5)


model6 <- lm(Highhabitat ~ GDP + I(GDP^2), data = data)

summary(model6)

anova(model6)


model7 <- lm(Low ~ GDP + I(GDP^2), data = data)

summary(model7)
```

```
anova(model7)


# Store coefficients and p-values for all models

results <- data.frame(

  Environment = c("Air Pollution", "Wastewater", "Forest Cover", "Soil Erosion",
"Impervious Land", "High Habitat", "Low Habitat"),

  Coef_Intercept = c(coef(model1)[1], coef(model2)[1], coef(model3)[1],
coef(model4)[1], coef(model5)[1], coef(model6)[1], coef(model7)[1]),

  Coef_GDP = c(coef(model1)[2], coef(model2)[2], coef(model3)[2],
coef(model4)[2], coef(model5)[2], coef(model6)[2], coef(model7)[2]),

  Coef_GDP2 = c(coef(model1)[3], coef(model2)[3], coef(model3)[3],
coef(model4)[3], coef(model5)[3], coef(model6)[3], coef(model7)[3]),

  P_value_GDP = c(summary(model1)$coefficients[2, 4],
summary(model2)$coefficients[2, 4], summary(model3)$coefficients[2, 4],

                  summary(model4)$coefficients[2, 4], summary(model5)$coefficients[2, 4],
summary(model6)$coefficients[2, 4],

                  summary(model7)$coefficients[2, 4]),

  P_value_GDP2 = c(summary(model1)$coefficients[3, 4],
summary(model2)$coefficients[3, 4], summary(model3)$coefficients[3, 4],

                   summary(model4)$coefficients[3, 4], summary(model5)$coefficients[3,
4], summary(model6)$coefficients[3, 4],

                   summary(model7)$coefficients[3, 4])
```

```
)

# Print and save the results
print(results)
write.csv(results, "EKC_results.csv", row.names = FALSE)

# Combine all environmental variables for final multi-panel EKC plot
library(reshape2)
environment_data <- data.frame(
  GDP = data$GDP,
  Air.pollution = data$airpollution,
  Wastewater = data$Wastewater,
  Forest.cover = data$forestcover,
  Soil.erosion = data$soilerosion,
  Impervious.land = data$Impervious,
  High.habitat = data$Highhabitat,
  Low.habitat = data$Low
)
```

```
environment_data_long <- melt(environment_data, id.vars = "GDP", variable.name =
"Variable")

ekc_plot <- ggplot(environment_data_long, aes(x = GDP, y = value, color =
Variable)) +
  geom_point() +
  geom_smooth(method = "lm", formula = y ~ x + I(x^2), se = FALSE) +
  labs(x = "Per Capita GDP (yuan)", y = "Environmental Indicator", color =
"Variable") +
  ggtitle("Environmental Kuznets Curve") +
  theme_minimal() +
  facet_wrap(~ Variable, scales = "free_y", ncol = 2)
print(ekc_plot)
```

6.3 Appendix C

Supplementary material: Chapter 4

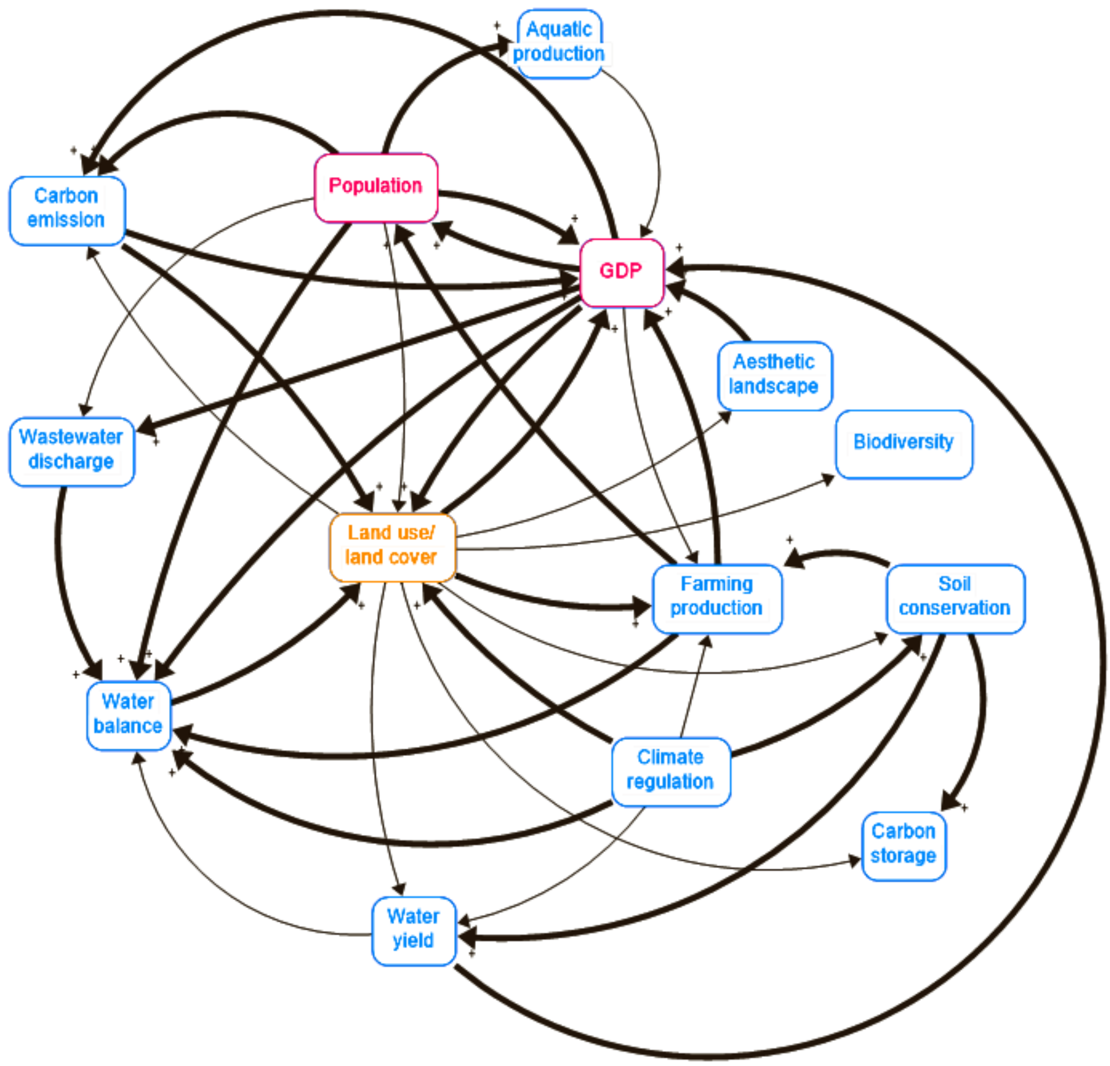


Figure 6.3-1 Module relationship from real model of ES and LULC.

6.3.1 Population, labor force, and land demand sub-model

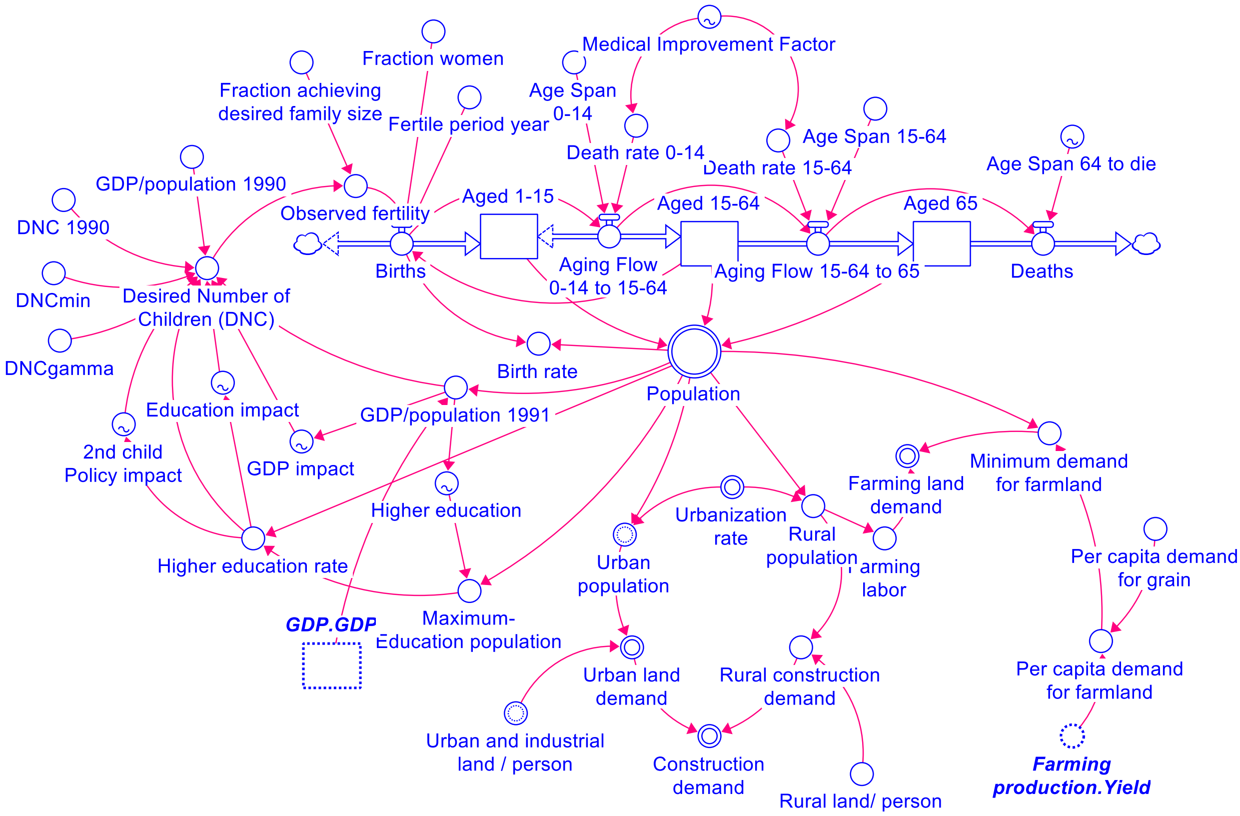


Figure 6.3-2 Structure of population, labor force, and land demand sub-model.

This sub-model captures how demographic transitions influence long-term land demand through shifts in labor supply and urbanization (see SI Figure 1). The core stock is population, which is disaggregated into three age cohorts: children (0–14 years), working-age adults (15–64 years), and the elderly (65+ years). Transitions between age groups occur through aging flows, while the overall population is dynamically adjusted through births and deaths. Birth rates are determined by the total fertility rate, which is modeled as a function of the desired number of children (DNC). The DNC is shaped by socioeconomic conditions, particularly education level, household income, and family planning policies (e.g., the two-child policy in China).

The working-age population constitutes the primary labor force for agriculture. However, the size and availability of this labor force are further influenced by access to higher education. As education levels rise and economic development accelerates, rural populations are increasingly drawn to urban areas, reducing the supply of agricultural labor. This urbanization process is endogenously modeled, driven by GDP growth and educational attainment.

Agricultural labor availability directly determines farmland demand, which is calculated based on per capita grain demand and farmland productivity. In parallel, growth in the urban population drives demand for construction land. Together, these two LULC demands reflect the broader spatial consequences of demographic and economic transitions.

By linking demographic structure, educational dynamics, labor mobility, and spatial land demand, the model offers a coherent framework to examine the trade-offs between farmland preservation and urban expansion under different socioeconomic scenarios.

6.3.2 LULC sub-model

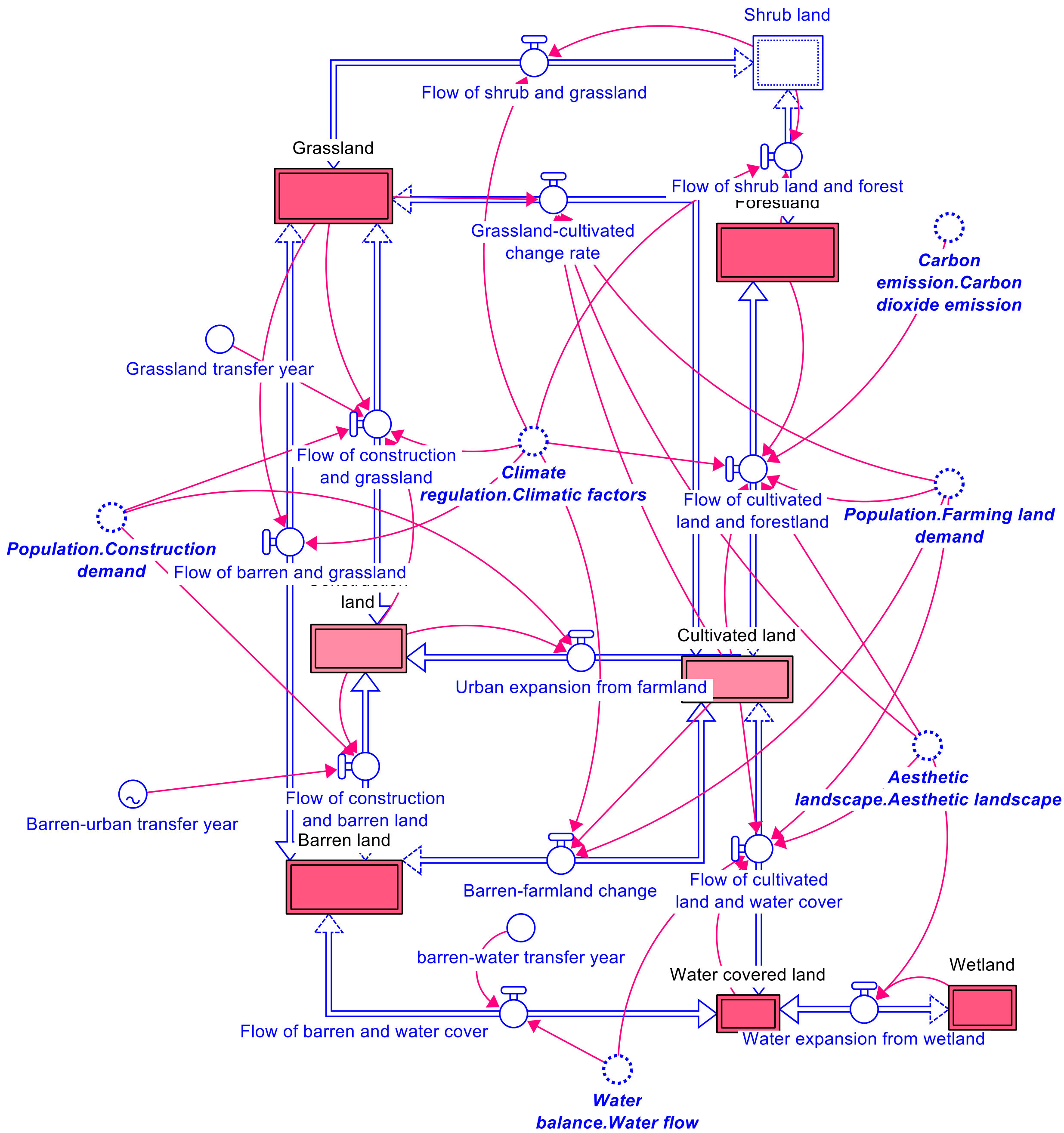


Figure 6.3-3 Structure of LULC transitions sub-model bases on ES Responses.

This sub-model simulates the dynamic transitions among six major LULC types—cultivated land, forestland, grassland, barren land, water-covered land, and wetlands—and their feedback interactions with key ecosystem services, including climate regulation, carbon emissions, water balance, and aesthetic landscape quality. Each LULC type is represented as a stock variable, and transitions between land types are governed by a set of flow variables reflecting biophysical, socioeconomic, and policy-driven processes.

Several dominant transition pathways are explicitly modeled. Urban expansion is driven by construction land demand, which converts grassland, barren land, and cultivated land into built-up areas. Cultivated–forest–water dynamics capture LULC shifts influenced by climate variability and hydrological conditions. Barren land redevelopment allows for conversion into cultivated land or water bodies, conditional on policy-defined time windows or ecological restoration triggers. Grassland transitions respond to both climatic drivers and population pressure, and may be directed toward forestland or agriculture, reflecting competition for land.

The model embeds feedback loops between land cover and ecosystem services. For example, land conversion alters carbon emissions, evapotranspiration rates, and landscape aesthetics, which in turn modify the drivers of future LULC change. These bidirectional feedbacks introduce nonlinearities and path dependencies into the land system dynamics.

This sub-model enables scenario-based simulations of land-use–ecosystem interactions, supporting analysis of policy interventions such as urban growth control, reforestation, wetland conservation, and agricultural intensification within an integrated socio-ecological framework.

6.3.3 GDP sub-model

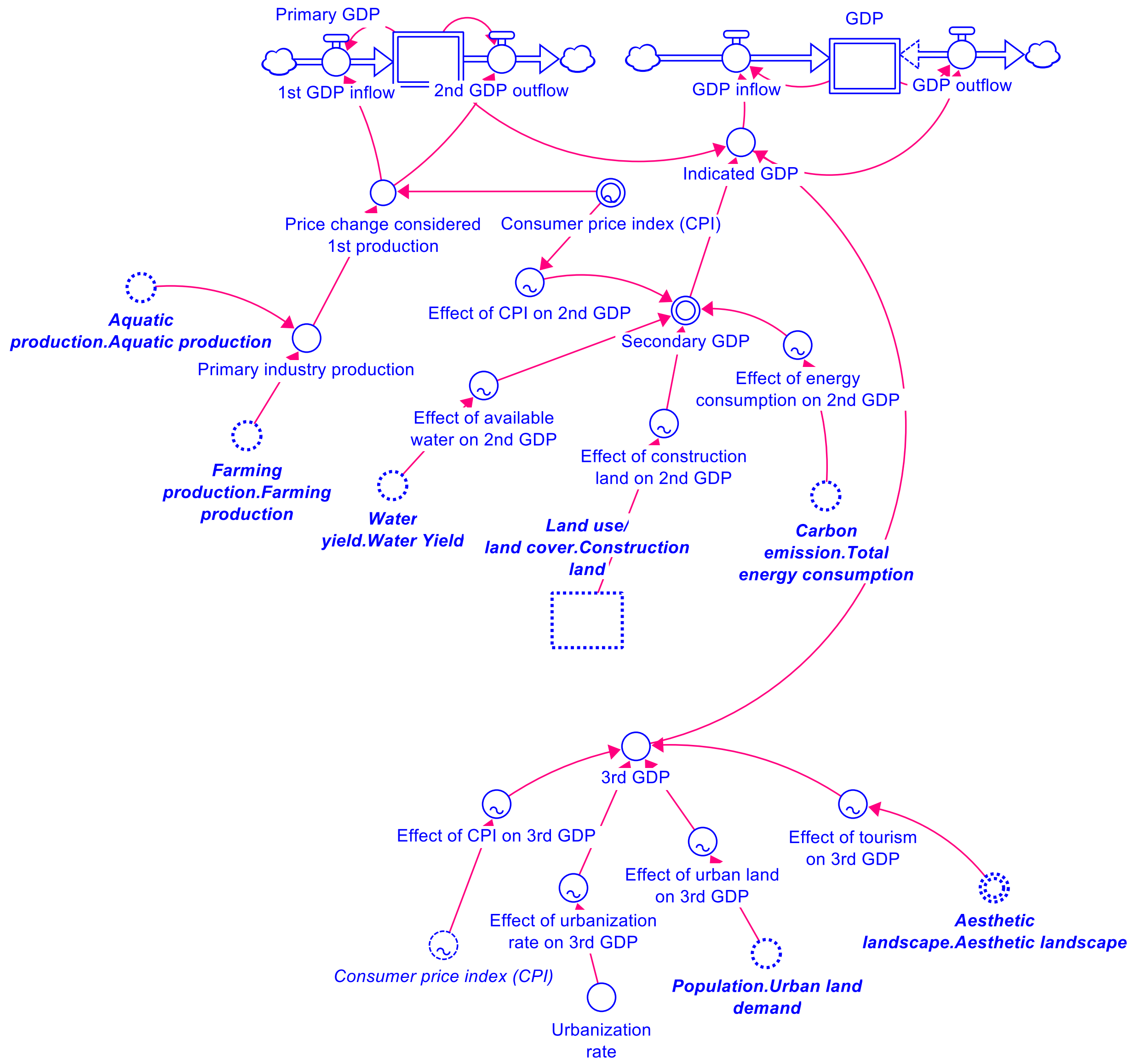


Figure 6.3-4 Structure of GDP sub-model, bases on land, resources, and prices.

This sub-model simulates the sectoral evolution of GDP and its dynamic interactions with land use, water resources, energy consumption, and price mechanisms (see SI Figure 3). GDP is disaggregated into three major sectors—primary, secondary, and tertiary—each governed by distinct but interconnected drivers. The primary sector is determined by outputs from farming and aquaculture systems, which are themselves influenced by land availability, water supply, and environmental conditions. The secondary sector is shaped by access to construction land, energy consumption, and water availability, reflecting the resource intensity of industrial development. The tertiary sector is driven by the extent of urban land, consumer price index (CPI), urbanization rate, and tourism activity, indicating the socio-spatial basis of service economies.

Land use—particularly construction and urban land—not only facilitates industrial and service sector growth, but is also restructured as a consequence of economic expansion, forming a bidirectional feedback loop. Meanwhile, CPI functions as a dynamic price signal, influencing real economic outputs and consumer behavior, and is itself sensitive to external shocks such as political instability or inflationary pressures. Water yield and carbon emissions act as critical ecological constraints that regulate the sustainability of GDP growth, particularly in resource-stressed regions.

The model explicitly incorporates feedback pathways between economic structure, LULC allocation, and environmental constraints, enabling scenario-based exploration of sustainable development trajectories. It supports the evaluation of integrated policy interventions aimed at balancing economic growth with environmental limits and LULC efficiency.

6.3.4 Farming production sub-model

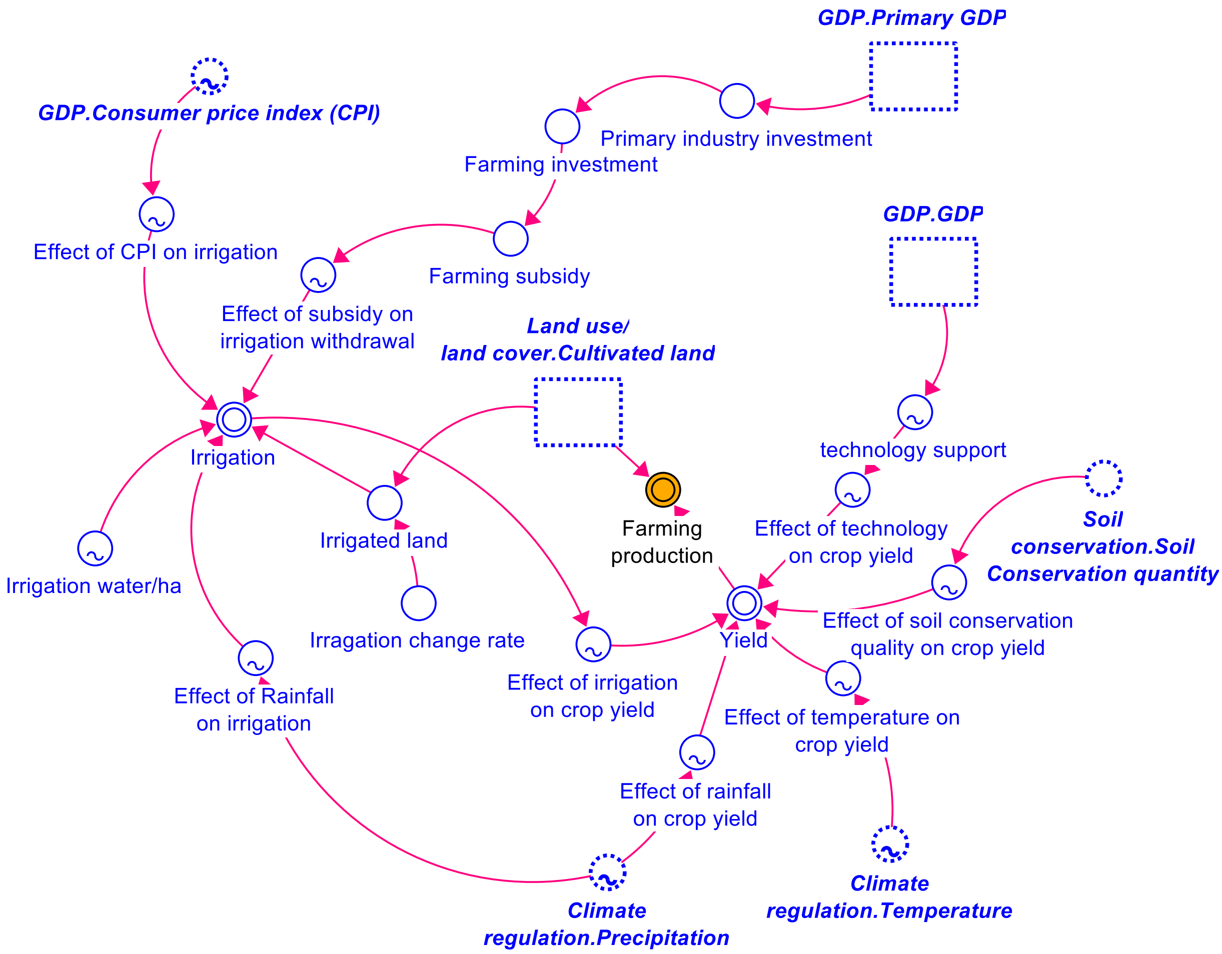


Figure 6.3-5 Structure of farming production sub-model under Irrigation, Climate, technological, and ecological feedbacks.

This sub-model captures the dynamics of agricultural production by linking climatic, ecological, technical, and economic drivers through an integrated system. Crop yield is modeled as a function of precipitation, temperature, soil conservation quality, and irrigation efficiency. The irrigation subsystem is jointly determined by water availability, cultivated land area, and farming subsidies, the latter two of which are influenced by consumer price index (CPI) and primary sector investment tied to GDP performance.

Technological support—represented by agricultural R&D and capital investment—directly enhances yield potential and interacts with irrigation efficiency. Soil conservation is introduced not only as a long-term ecological buffer but also as a key modulator of yield response to climate stress. Meanwhile, farming subsidies, CPI, and water resources are embedded in feedback loops that regulate the allocation of agricultural land and productivity over time.

By integrating these dimensions, the model simulates how agricultural output adapts to climate variability, economic fluctuations, and policy interventions. It provides a dynamic framework to assess system resilience, particularly in the face of water scarcity, inflationary pressures, and ecological degradation.

6.3.5 Water yield sub-model

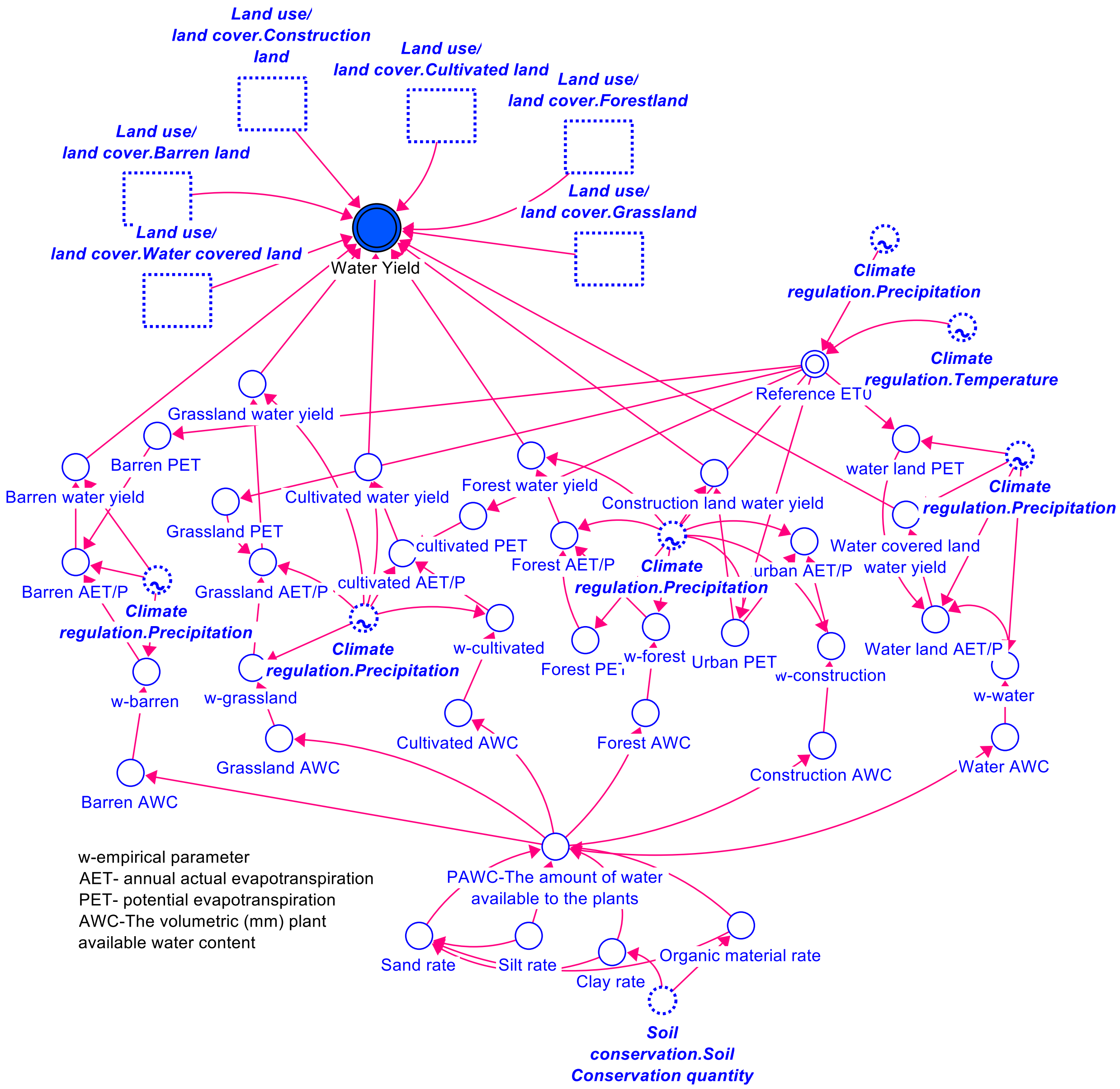


Figure 6.3-6 Water yield sub-model, bases on InVEST model- Water Yield section.

This module is adapted from the InVEST Annual Water Yield model, which estimates annual water yield across different land use/land cover (LULC) types using a Budyko-based water balance framework. In this study, the pixel-based InVEST logic is translated into a system dynamics structure, in which each land type is assigned specific equations and parameters. The model captures key hydrological interactions among precipitation, evapotranspiration, vegetation, soil properties, and land use, and computes both land-type-specific water yield and total regional yield.

1. **Core Water Yield Equation**

The annual water yield $Y(x)$ for each land use type x is calculated as the difference between precipitation and actual evapotranspiration (AET):

$$Y(x) = \left(1 - \frac{AET(x)}{P(x)}\right) \cdot P(x) \quad \text{......(1)}$$

Where:

Y(x) is the annual water yield per unit area for land type x;

P(x) is annual precipitation;

AET(x) is actual annual evapotranspiration.

2. **Actual Evapotranspiration (AET)**

a. For vegetated land types (e.g., forest, grassland, cultivated land), AET is calculated using the Fu-Budyko equation (Fu, 1981; Zhang et al., 2004)

$$\frac{AET(x)}{P(x)} = 1 + \frac{PET(x)}{P(x)} - \left[1 + \left(\frac{PET(x)}{P(x)}\right)^{\omega}\right]^{\frac{1}{\omega}} \quad \text{......(2)}$$

where PET(x) is the potential evapotranspiration and ω(x) is a non-physical parameter that characterizes the natural climatic-soil properties, both detailed below.

b. For other LULC types (open water, urban, wetland), actual evapotranspiration is directly computed from reference evapotranspiration ET0(x) and has an upper limit defined by precipitation:

$$AET(x) = min(Kc(x) \cdot ET0(x), P(x))$$

where ET0(x) is reference evapotranspiration, and Kc(ℓx) is the evaporation factor for each LULC.

3. Potential evapotranspiration PET(x):

Potential evapotranspiration is derived from the reference evapotranspiration (ET0(x)) and the crop/vegetation coefficient (Kc(lx)):

$PET(x) = Kc(\ell x) \cdot ET0(x)$……………………………………………………(3)

ET0(x): Reference evapotranspiration, based on local climatic data (e.g., temperature, radiation);

Kc(x): Coefficient adjusting ET0 to the specific LULC type, based on vegetation properties (Allen et al., 1998).

4. Empirical Parameter ω(x)

ω(x) is an empirical parameter that can be expressed as linear function of AWC∗NP, where N is the number of rain events per year, and AWC is the volumetric plant available water content (see Appendix 1 for additional details). While further research is being conducted to determine the function that best describe global data, this study use the expression proposed by Donohue et al. (2012) in the InVEST model, and thus define:

$\omega(x) = Z\frac{AWC(x)}{P(x)} + 1.25$…………………………………………………………(4)

where:

AWC(x): Plant available water content (mm);

P(x): Annual precipitation;

Z: Seasonality factor;

1.25: Minimum value for bare soil (Donohue et al., 2012).

Values of ω(x) are capped at 5, following Yang et al. (2008).

Z is an empirical constant, sometimes referred to as "seasonality factor", which captures the local precipitation pattern and additional hydrogeological characteristics. It is positively correlated with N, the number of rain events per year. The 1.25 term is the minimum value of ω(x), which can be seen as a value for bare soil (when root depth is 0), as explained by Donohue et al. (2012). Following the literature (Yang et al., 2008; Donohue et al. 2012), values of ω(x) are capped to a value of 5.

5. Plant Available Water Content (AWC)

AWC(x) is the volumetric (mm) plant available water content. The soil texture and effective rooting depth define AWC(x), which establishes the amount of water that can be held and released in the soil for use by a plant. It is estimated as the product of the plant available water capacity (PAWC) and the minimum of root restricting layer depth and vegetation rooting depth:

$$AWC(x) = Min(Rest.layer.depth, root.depth) \cdot PAWC \ldots\ldots\ldots\ldots (5)$$

Root restricting layer depth is the soil depth at which root penetration is inhibited because of physical or chemical characteristics. Vegetation rooting depth is often given as the depth at which 95% of a vegetation type's root biomass occurs. PAWC is the plant available water capacity, i.e. the difference between field capacity and wilting point.

In this model, AWC is set as 0.5 × PAWC for barren land, 2.5 × PAWC for grassland, 3.5 × PAWC for cultivated land, and 5.2 × PAWC for forest land. For non-vegetated land use types such as construction land and water-covered land, AWC is fixed at 0.1 × PAWC. These multipliers reflect the relative water-holding capacity of each land use type based on typical root zone depth and soil-plant interactions.

6. PAWC Estimation Formula

PAWC is estimated from soil texture and organic matter content using the following empirical equation:

$PAWC = 54.509 - 0.132 \cdot S - 0.003 \cdot S^2 - 0.055 \cdot Si - 0.006 \cdot Si^2 + 0.738 \cdot C - 0.007 \cdot C^2 - 2.688 \cdot OM + 0.501 \cdot OM^2$ ……………………………………(6)

Where:

S: sand content (%); Si: silt content (%); C: clay content (%); OM: organic matter (%).

This formulation allows AWC to dynamically respond to soil composition across different land units.

7. Regional Water Yield Aggregation (weighted sum)

The total annual water yield for the region is computed as a weighted sum of land-type-specific water yields:

$Water\ yield_{total} = \frac{\sum_x Y(x) * A(x)}{Land}$………………………………………………(7)

Where:

- Y(x): unit water yield for land type x;
- A(x): total area of land type x;
- Land: total area of the study region: 15,463,289 hm.

By structurally embedding InVEST's pixel-level hydrological logic into a stock–flow framework, this module provides a pioneering pathway for coupling LULC transitions with water resource dynamics in long-term socio-ecological simulations.

6.3.6 Water flow balance sub-model

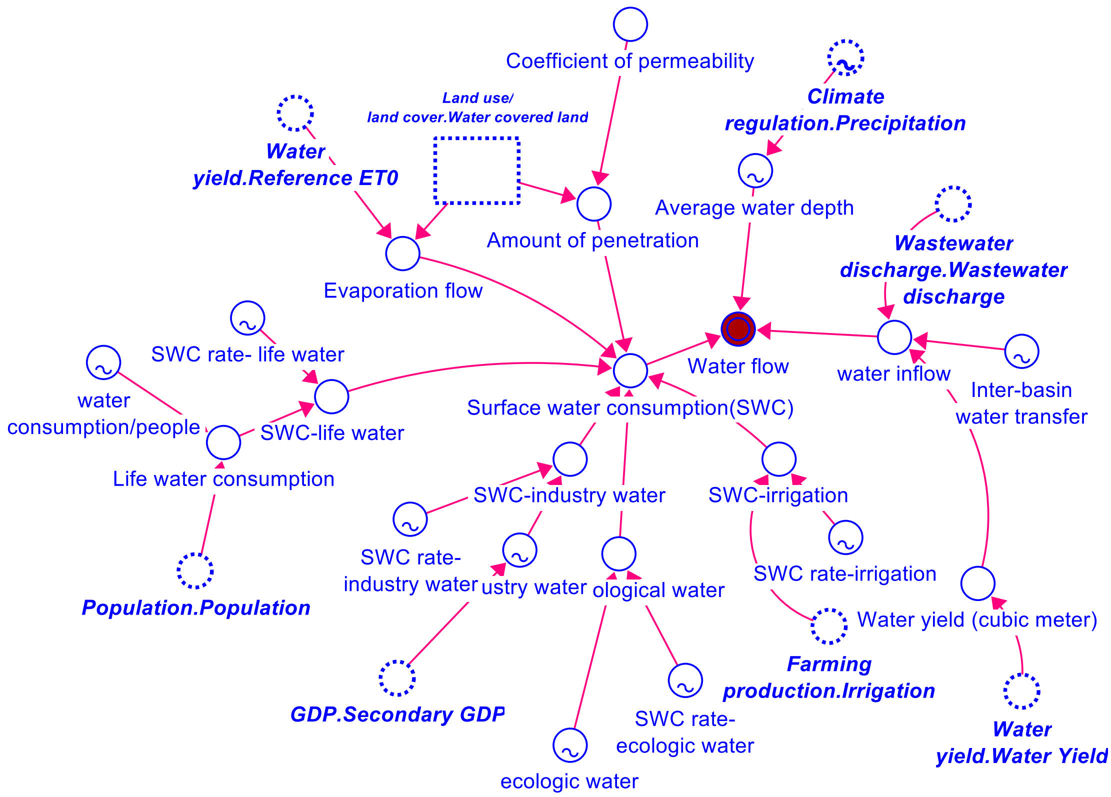


Figure 6.3-7 Water flow balance sub-model, based on water flow and surface water consumption under climate, population, and economic drivers.

This sub-model captures the dynamic water balance of the region by simulating the evolution of surface water resources and their consumption across key socio-ecological sectors (Figure 7-21). The central stock variable, Water Flow, represents the available surface water volume in the system. This stock is increased by multiple inflows: (i) natural water yield derived from the water yield module (driven by precipitation, evapotranspiration, and land cover); (ii) wastewater returns from domestic and industrial systems; and (iii) inter-basin water transfer projects. Water is depleted from the stock through (i) evaporation (a function of surface area and temperature), (ii) infiltration to soil and groundwater, and (iii) surface water consumption (SWC).

SWC is further disaggregated into four flow components: (1) domestic water use, modeled as a function of per capita water use and total population; (2) industrial water use, linked to the scale and growth of the secondary economic sector (secondary

GDP); (3) irrigation water demand, calculated based on cultivated land area and irrigation efficiency; and (4) ecological water use, allocated based on predefined policy targets for environmental flow requirements. Each component contributes to the reduction of the Water Flow stock and responds dynamically to socioeconomic or climatic drivers.

This structure enables integrated simulations of surface water dynamics under varying climate, land use, and development trajectories. It also allows for testing the effectiveness of water-saving policies (e.g., irrigation efficiency improvement, industrial upgrading, ecological redlines) in mitigating regional water stress and maintaining hydrological stability across long-term scenarios.

6.3.7 Carbon storage sub-model

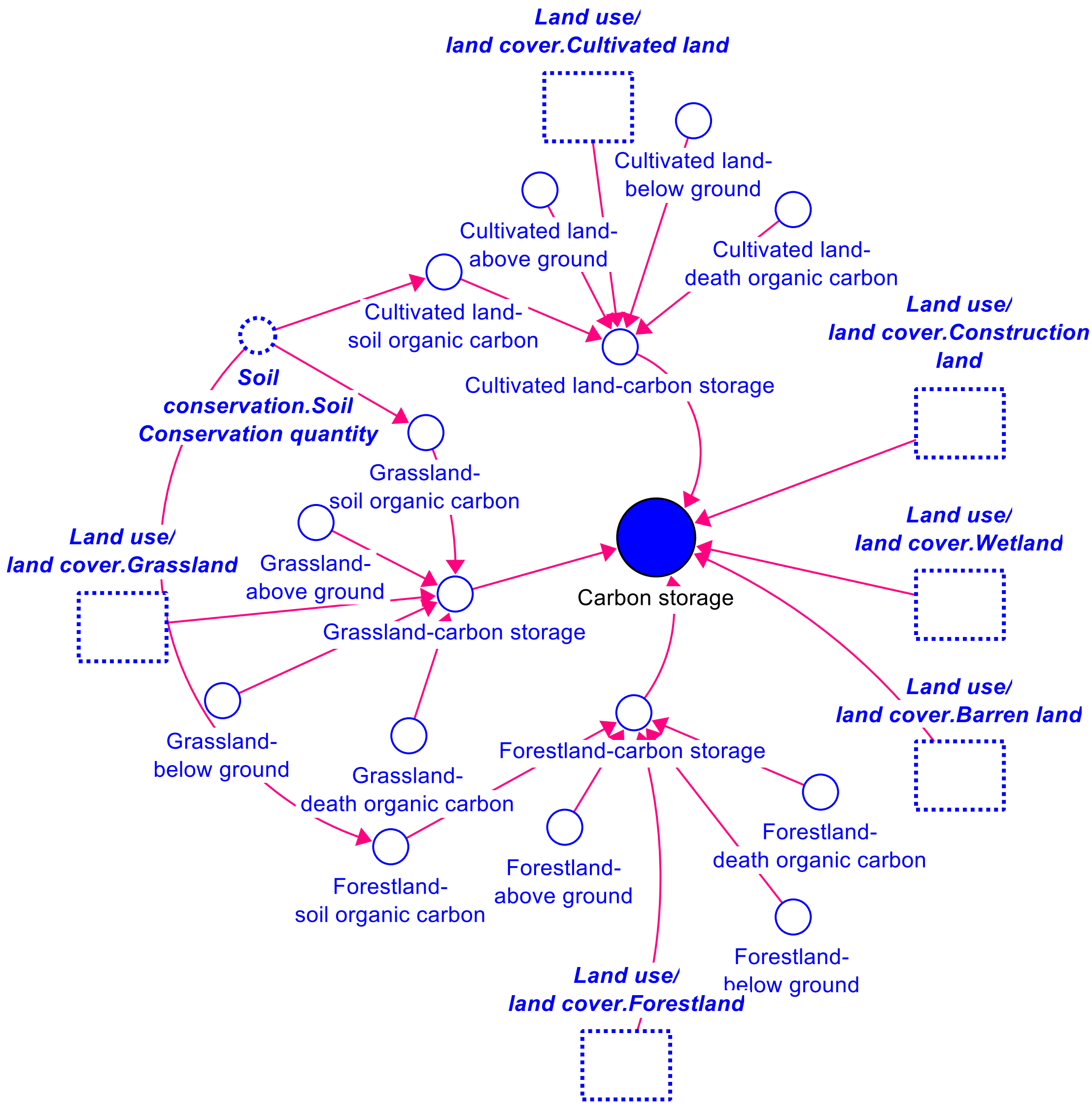


Figure 6.3-8 Carbon storage sub-model, based on InVEST model-Carbon section.

This carbon storage module is adapted from the **InVEST Carbon Storage and Sequestration model**, which estimates total carbon stock by combining land use/land cover (LULC) types with their respective carbon pool densities. In the system dynamics framework, each land type contributes to total carbon storage through four distinct carbon pools:

$$C_{total} = \sum A_x * (C_{above,x} + C_{below,x} + C_{dead,x} + C_{soil,x})$$

Where:

- C_total: Total carbon storage (tC);
- Ax: Area of LULC type xxx;
- Cabove,x, Cbelow,x, Cdead,x, Csoil,x: Aboveground, belowground, dead organic, and soil organic carbon densities (tC/ha).

In this model:

- All major LULC types (e.g., forest, grassland, cropland) are associated with static or scenario-updated carbon densities per pool;
- Carbon pool values are parameterized based on empirical data or national inventories;
- The system dynamically updates total carbon storage in response to land use transitions over time.

Optionally, soil conservation quantity can be used to adjust soil carbon as:

$$C_{soil,adjusted} = C_{soil} \cdot (1 + \theta \cdot SQ)$$

Where SQ is the soil conservation index, and θ is a sensitivity coefficient.

This structure supports policy-relevant scenario simulations such as afforestation, reforestation, land degradation, or agricultural expansion, providing insights into ecosystem carbon trade-offs and climate mitigation potential.

6.3.8 Soil conservation quantity sub-section.

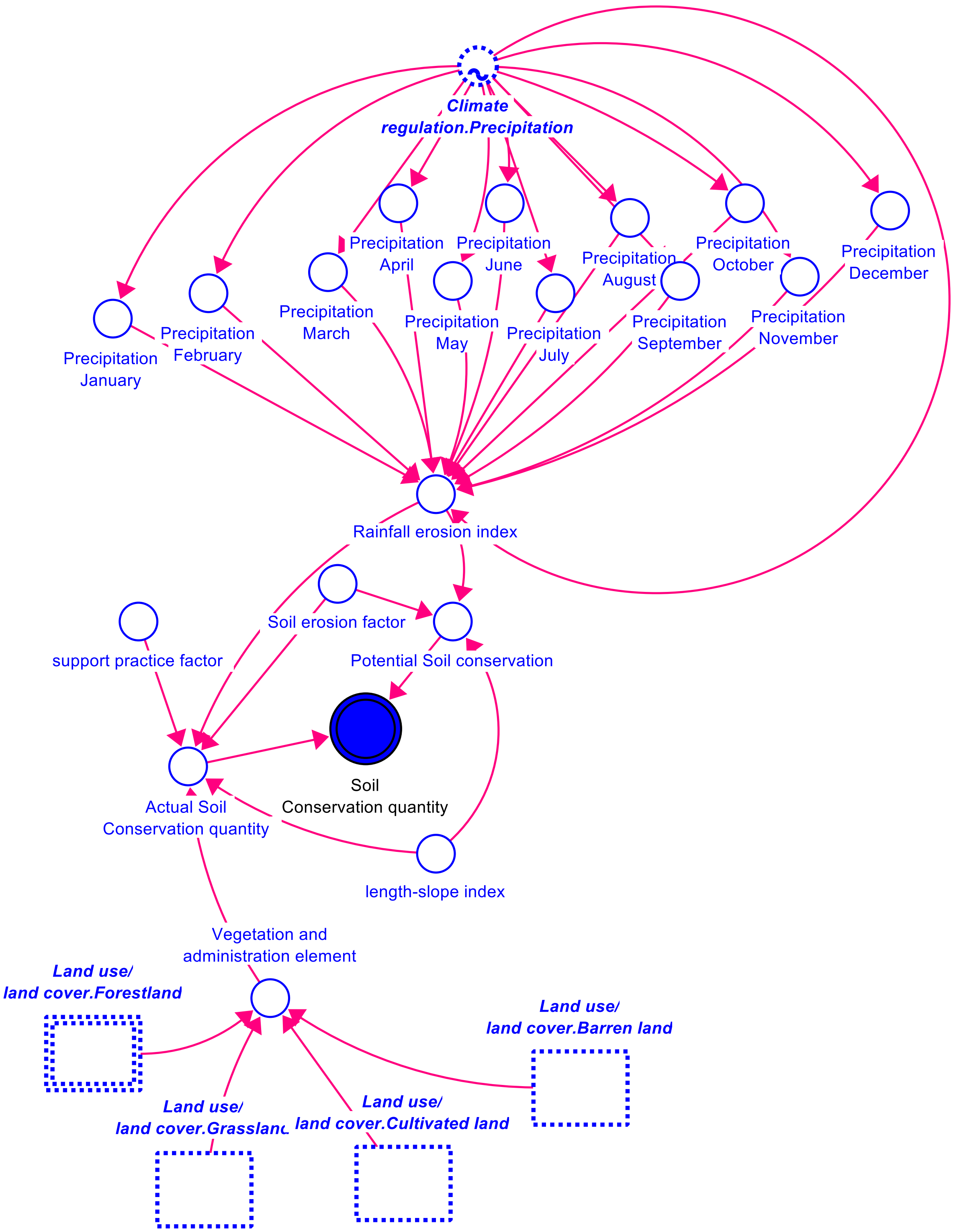


Figure 6.3-9 Soil conservation quantity sub-section.

This sub-model translates the InVEST Sediment Retention model into a system dynamics framework to estimate regional soil conservation services based on land use, topography, rainfall, and land management practices (Figure 7-23). The model captures monthly rainfall variability, topographic conditions, and vegetation dynamics to simulate both potential and actual soil loss using the RUSLE (Revised Universal Soil Loss Equation) approach.

In this system dynamics implementation, total annual precipitation is disaggregated into 12 monthly values, contributing to a **Rainfall Erosion Index (R)**. Combined with land surface factors, this index drives the calculation of both potential and actual soil loss using the **Revised Universal Soil Loss Equation (RUSLE)** framework:

$$Potential\ Soil\ Loss = R \cdot K \cdot LS$$

$$Actual\ Soil\ Loss = R \cdot K \cdot LS \cdot C \cdot P$$

Where:

- R: Rainfall erosion index (sum of monthly rainfall erosivity);
- K: Soil erodibility factor;
- LS: Topographic factor (length-slope index);
- C: Vegetation cover and management factor;
- P: Support practice factor.

The **Soil Conservation Quantity** is then:

$$Soil\ Conservation = Potential\ Soil\ Loss - Actual\ Soil\ Loss$$

Land use/land cover types (e.g., forest, grassland, cultivated land, barren land) are associated with specific C and P values based on vegetation cover and land management intensity. This structure allows the model to capture seasonal and inter-annual variability in soil retention capacity driven by precipitation dynamics and LULC transitions. It enables scenario analysis of soil erosion risk under climate change, deforestation, agricultural intensification, or conservation interventions.

6.3.9 Energy consumption and carbon emissions sub-model

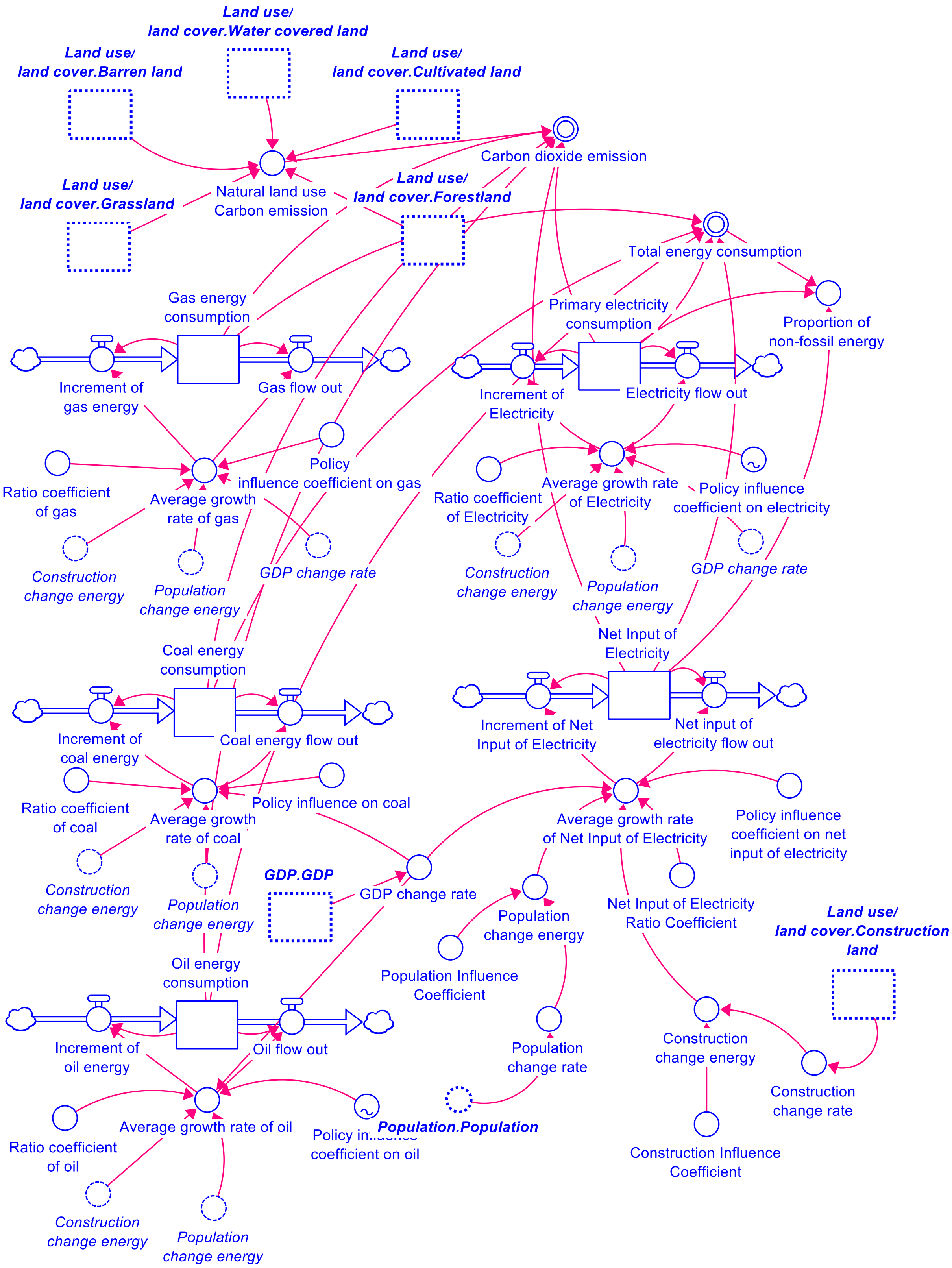


Figure 6.3-10 Energy consumption and carbon emissions sub-model of bases on socioeconomic drivers.

This model simulates the dynamics of total energy consumption and carbon dioxide emissions by integrating four primary energy sources—coal, oil, gas, and electricity—with land use, population, GDP, and policy interventions. Each energy source is represented as a stock variable (e.g., coal energy consumption), with inflows determined by growth rates that are functions of construction demand, population change, GDP change, and policy influence coefficients. The flow-out terms represent energy consumption or export.

Electricity is further divided into domestic generation (primary electricity consumption) and net input of electricity (e.g., imports), with its share influencing the proportion of non-fossil energy. All four energy streams contribute to total energy consumption, which, along with land-based carbon sources (from different LULC types), drives carbon dioxide emissions. Research on the energy consumption model structure reference Liu et al. (2015)'s research.

Land use (e.g., forest, cultivated, barren, water, grassland) contributes to natural LULC carbon emissions, linking energy-driven emissions with LULC change. The model enables scenario analysis of how shifts in socioeconomic development, energy structure, and land cover affect carbon outcomes under varying policy settings. Carbon density of vegetation in different land cover types from the research of Liu et al. (2022a).

6.3.10 Description of feedback loops identified in the real model

Table 6.3-1 Description of feedback loops identified in the real model.

Loops	Description
Reinforcing feedback loops	
R1	GDP growth → (+) Agricultural inputs/technology → (+) Crop yield → (+) Agricultural production → (+) Agricultural GDP → (+) GDP growth

R2	Water covered land → (+) Aesthetic landscape → (+) Tourism required water landscape → (+) Water covered land
Balancing feedback loops	
B1	Construction land → (–) Farmland → (–) Construction land
B2	Construction land → (–) Barren land → (–) Construction land
B3	Construction land → (–) Grassland → (–) Construction land
B4	Population → (+) Urbanisation → (–) Agricultural labour → (–) Farmland → (+) Agricultural intensification → (+) Agricultural production → (+) Economic growth → (–) Fertility/birth rate → (–) Population
B5	Population → (+) Urbanisation → (+) Construction land → (–) Farmland → (+) Agricultural intensification → (+) Agricultural production → (+) Economic growth → (–) Fertility/birth rate → (–) Population
B6	Population → (+) Construction land → (–) Water yield → (–) Farmland security → (+) Agricultural intensification → (+) Agricultural production → (+) Economic growth → (–) Fertility/birth rate → (–) Population
B7	Population → (+) Construction land → (+) Carbon emissions → (+) Carbon-neutrality policy → (+) Cropland-to-forest conversion → (–) Farmland → (+) Agricultural intensification → (+) Agricultural production → (+) Economic growth → (–) Fertility/birth rate → (–) Population

B8	Population → (+) Construction land → (–) Farmland → (+) Forest land → (+) Landscape aesthetics → (+) Water bodies → (+) Fisheries production → (+) GDP → (–) Fertility/birth rate → (–) Population

Table 6.3-2 Model Structural Summary and Component Statistics

Total	Count	Including Array Elements
Variables	337	337
Modules	14	
Stocks	19	19
Flows	30	30
Converters	288	288
Constants	33	33
Equations	285	285
Graphicals	53	53
Macro Variables	87	

6.3.11 Equations of the ES-LULC SD model.

Figure 6.3-3 Equations of the ES-LULC SD model.

	Equation	Properties	Units
Top-Level Model:			
Aesthetic_landscape:			
Aesthetic_landscape	120.07*"Land_use/_land_cover".Cultivated_land+1751.06*"Land_use/_land_cover".Forestland+1180.72*"Land_use/_land_cover".Grassland+10426.32*("Land_use/_land_cover".Water_covered_land+"Land_use/_land_cover".Wetland)+"Land_use/_land_cover".Barren_land*140.08+"Land_use/_land_cover".Construction_land*398		CNY·hm-2 · a -1
Aquatic_production:			
Water_covered_land(t)	Water_covered_land(t - dt)	INIT Water_cove	ha

		red_land = 362359	
Aquatic_product_demand	Population.Population*"Aquatic_production_local_demand/yr"		
Aquatic_production	Freshwater_aquatic_production+Sea_aquatic_production		
Aquatic_production_for_Other_province_support_and_export	Aquatic_production-Aquatic_product_demand		
"Aquatic_production_local_demand/yr"	0.01473		ton/yr
Freshwater_aquatic_production	GRAPH(Water_covered_land) Points: (255707, 202000), (261848.62069, 261700), (267990.241379, 320200), (274131.862069, 377400), (280273.482759, 433200), (286415.103448, 487900), (292556.724138, 541300), (298698.344828, 593600), (304839.965517, 644700), (310981.586207, 694700), (317123.206897, 743500), (323264.827586, 791300), (329406.448276, 838000), (335548.068966, 883700), (341689.689655, 928400), (347831.310345, 972100), (353972.931034, 1015000), (360114.551724, 1057000), (366256.172414, 1097000), (372397.793103, 1137000), (378539.413793, 1176000), (384681.034483, 1215000), (390822.655172, 1252000), (396964.275862, 1288000), (403105.896552, 1324000), (409247.517241, 1359000), (415389.137931, 1393000), (421530.758621, 1427000), (427672.37931, 1459000), (433814, 1491000)		tons
Sea_aquatic_production	GRAPH(Temperature) Points: (13.260, 1780000), (13.4924137931, 3320000), (13.7248275862, 5600000), (13.9572413793, 6910000), (14.1896551724, 7680000), (14.4220689655, 8040000), (14.6544827586, 8220000), (14.8868965517, 8390000), (15.1193103448, 8390000), (15.3517241379, 8200000), (15.584137931, 8020000), (15.8165517241, 7910000), (16.0489655172, 7790000), (16.2813793103, 7530000), (16.5137931034, 7270000), (16.7462068966, 7120000), (16.9786206897, 6890000), (17.2110344828, 6630000), (17.4434482759, 6330000), (17.675862069, 6110000), (17.9082758621, 5880000), (18.1406896552, 5690000), (18.3731034483, 5430000),		

	(18.6055172414, 5210000), (18.8379310345, 4980000), (19.0703448276, 4800000), (19.3027586207, 4610000), (19.5351724138, 4310000), (19.7675862069, 4120000), (20.000, 3930000)		
Temperature	GRAPH(TIME) Points: (31.00, 14.120), (33.724137931, 14.160), (36.4482758621, 14.200), (39.1724137931, 14.250), (41.8965517241, 14.290), (44.6206896552, 14.330), (47.3448275862, 14.370), (50.0689655172, 14.410), (52.7931034483, 14.460), (55.5172413793, 14.500), (58.2413793103, 14.540), (60.9655172414, 14.580), (63.6896551724, 14.620), (66.4137931034, 14.670), (69.1379310345, 14.710), (71.8620689655, 14.750), (74.5862068966, 14.790), (77.3103448276, 14.840), (80.0344827586, 14.880), (82.7586206897, 14.920), (85.4827586207, 14.960), (88.2068965517, 15.000), (90.9310344828, 15.050), (93.6551724138, 15.090), (96.3793103448, 15.130), (99.1034482759, 15.170), (101.827586207, 15.210), (104.551724138, 15.260), (107.275862069, 15.300), (110.00, 15.340)		
Biodiversity:			
Biodiversity	"Land_use/_land_cover".Cultivated_land*260.16+"Land_use/_land_cover".Forestland*3982.41+"Land_use/_land_cover".Grassland*2674.96+("Land_use/_land_cover".Water_covered_land+"Land_use/_land_cover".Wetland)*10426.32+"Land_use/_land_cover".Barren_land*140.08		CNY·hm-2·a-1
Carbon_emission:			
Coal_energy_consumption(t)	Coal_energy_consumption(t - dt) + (Increment_of_coal_energy - Coal_energy_flow_out) * dt	INIT Coal_energy_consumption = 28031387 8	
Gas_energy_consumption(t)	Gas_energy_consumption(t - dt) + (Increment_of_gas_energy - Gas_flow_out) * dt	INIT Gas_energy_consumption = 2439 9791	

Net_Input_of_Electricity(t)	Net_Input_of_Electricity(t - dt) + (Increment_of_Net_Input_of_Electricity - Net_input_of_electricity_flow_out) * dt	INIT Net_Input_of_Electricity = 39153153	
Oil_energy_consumption(t)	Oil_energy_consumption(t - dt) + (Increment_of_oil_energy - Oil_flow_out) * dt	INIT Oil_energy_consumption = 74377896	
Primary_electricity_consumption(t)	Primary_electricity_consumption(t - dt) + (Increment_of_Electricity - Electricity_flow_out) * dt	INIT Primary_electricity_consumption = 18245282	
Coal_energy_flow_out	-Average_growth_rate_of_coal*Coal_energy_consumption		
Electricity_flow_out	-Average_growth_rate_of_Electricity*Primary_electricity_consumption		
Gas_flow_out	-Average_growth_rate_of_gas*Gas_energy_consumption		
Increment_of_coal_energy	Coal_energy_consumption*Average_growth_rate_of_coal		
Increment_of_Electricity	Primary_electricity_consumption*Average_growth_rate_of_Electricity		
Increment_of_gas_energy	IF TIME <25 THEN 0 ELSE Gas_energy_consumption*Average_growth_rate_of_gas		
Increment_of_Net_In	IF TIME <25 THEN 0 ELSE Net_Input_of_Electricity*(Average_growth_rate_of_Net_In		

put_of_Electricity	put_of_Electricity-DELAY(Average_growth_rate_of_Net_Input_of_Electricity, 1))		
Increment_of_oil_energy	Oil_energy_consumption*Average_growth_rate_of_oil		
Net_input_of_electricity_flow_out	-Average_growth_rate_of_Net_Input_of_Electricity*Net_Input_of_Electricity		
Oil_flow_out	-Average_growth_rate_of_oil*Oil_energy_consumption		
Average_growth_rate_of_coal	0.6*Ratio_coefficient_of_coal*GDP_change_rate+Population_change_energy+Construction_change_energy +Policy_influence_on_coal		
Average_growth_rate_of_Electricity	Ratio_coefficient_of_Electricity*GDP_change_rate*0.6+Population_change_energy+Construction_change_energy+Policy_influence_coefficient_on_electricity		
Average_growth_rate_of_gas	IF TIME <25 THEN 0.6*Ratio_coefficient_of_gas*GDP_change_rate+Population_change_energy+Construction_change_energy ELSE 0.6*Ratio_coefficient_of_gas*GDP_change_rate+Population_change_energy+Construction_change_energy+Policy_influence_coefficient_on_gas		
Average_growth_rate_of_Net_Input_of_Electricity	Net_Input_of_Electricity_Ratio_Coefficient*GDP_change_rate*0.6+Population_change_energy+Construction_change_energy+Policy_influence_coefficient_on_net_input_of_electricity		
Average_growth_rate_of_oil	0.6*Ratio_coefficient_of_oil*GDP_change_rate+Population_change_energy+Construction_change_energy+Policy_influence_coefficient_on_oil		
Carbon_dioxide_emission	(((Coal_energy_consumption*1000)*(0.7143)*(0.7559) +(Oil_energy_consumption*1000)*1.4286*0.5857 +((Primary_electricity_consumption+Net_Input_of_Electricity)*1000)*0.1229*0.007935 +(Gas_energy_consumption*1000)*1.2143*0.4483)/1000+ Natural_land_use_Carbon_emission)		
Construction_change_energy	Construction_change_rate*Construction_Influence_Coefficient		

Construction_change_rate	("Land_use/_land_cover".Construction_land-DELAY("Land_use/_land_cover".Construction_land, 1))/DELAY("Land_use/_land_cover".Construction_land, 1)		
Construction_Influence_Coefficient	1.5		
GDP_change_rate	(GDP.GDP-DELAY(GDP.GDP, 1))/DELAY(GDP.GDP, 1)		
Natural_land_use_Carbon_emission	"Land_use/_land_cover".Cultivated_land*0.422+"Land_use/_land_cover".Forestland*(-0.644)+"Land_use/_land_cover".Grassland*(-0.021)+"Land_use/_land_cover".Water_covered_land*(-0.253)+"Land_use/_land_cover".Barren_land*(-0.005)		ton
Net_Input_of_Electricity_Ratio_Coefficient	-0.155 * EXP(-9.49e-15 * (TIME - 1)) * SIN(1.266 * (TIME - 1) - 0.412) + 0.159		
Policy_influence_coefficient_on_electricity	GRAPH(TIME) Points: (1.00, 0), (2.00, 0), (3.00, 0), (4.00, 0), (5.00, 0), (6.00, 0), (7.00, 0), (8.00, 0), (9.00, 0), (10.00, 0), (11.00, 0), (12.00, 0), (13.00, 0), (14.00, 0), (15.00, 0), (16.00, 0), (17.00, 0), (18.00, 0), (19.00, 0), (20.00, 0), (21.00, 0), (22.00, 0), (23.00, 0), (24.00, 0), (25.00, 0), (26.00, 0), (27.00, 0), (28.00, 0), (29.00, 0), (30.00, 0), (31.00, 0), (32.00, 0), (33.00, 0), (34.00, 0), (35.00, 0), (36.00, 0), (37.00, 0), (38.00, 0), (39.00, 0), (40.00, 0), (41.00, 0), (42.00, 0), (43.00, 0), (44.00, 0), (45.00, 0), (46.00, 0), (47.00, 0), (48.00, 0), (49.00, 0), (50.00, 0), (51.00, 0), (52.00, 0), (53.00, 0), (54.00, 0), (55.00, 0), (56.00, 0), (57.00, 0), (58.00, 0), (59.00, 0), (60.00, 0), (61.00, 0), (62.00, 0), (63.00, 0), (64.00, 0), (65.00, 0), (66.00, 0), (67.00, 0), (68.00, 0), (69.00, 0), (70.00, 0), (71.00, 0), (72.00, 0), (73.00, 0), (74.00, 0), (75.00, 0), (76.00, 0), (77.00, 0), (78.00, 0), (79.00, 0), (80.00, 0)		
Policy_influence_coefficient_on_gas	-0.017		
Policy_influence_coefficient_on_net_input_of_electricity	0.109		
Policy_influence_coef	GRAPH(TIME) Points: (30.00, 0.0000), (31.00, -0.000484), (32.00, -0.0009803), (33.00, -0.001489), (34.00, -0.002011),		

ficient_on_oil	(35.00, -0.002546), (36.00, -0.003094), (37.00, -0.003657), (38.00, -0.004233), (39.00, -0.004824), (40.00, -0.005431), (41.00, -0.006052), (42.00, -0.006689), (43.00, -0.007343), (44.00, -0.008013), (45.00, -0.0087), (46.00, -0.009404), (47.00, -0.01013), (48.00, -0.01087), (49.00, -0.01163), (50.00, -0.0124), (51.00, -0.0132), (52.00, -0.01402), (53.00, -0.01486), (54.00, -0.01572), (55.00, -0.0166), (56.00, -0.01751), (57.00, -0.01843), (58.00, -0.01938), (59.00, -0.02036), (60.00, -0.02136), (61.00, -0.02238), (62.00, -0.02343), (63.00, -0.02451), (64.00, -0.02561), (65.00, -0.02675), (66.00, -0.02791), (67.00, -0.0291), (68.00, -0.03032), (69.00, -0.03157), (70.00, -0.03285), (71.00, -0.03417), (72.00, -0.03552), (73.00, -0.0369), (74.00, -0.03832), (75.00, -0.03977), (76.00, -0.04127), (77.00, -0.04279), (78.00, -0.04436), (79.00, -0.04597), (80.00, -0.04762), (81.00, -0.04931), (82.00, -0.05104), (83.00, -0.05281), (84.00, -0.05463), (85.00, -0.0565), (86.00, -0.05842), (87.00, -0.06038), (88.00, -0.06239), (89.00, -0.06445), (90.00, -0.06657), (91.00, -0.06874), (92.00, -0.07096), (93.00, -0.07324), (94.00, -0.07558), (95.00, -0.07798), (96.00, -0.08044), (97.00, -0.08296), (98.00, -0.08554), (99.00, -0.08819), (100.00, -0.09091), (101.00, -0.09369), (102.00, -0.09655), (103.00, -0.09948), (104.00, -0.1025), (105.00, -0.1056), (106.00, -0.1087), (107.00, -0.1120), (108.00, -0.1153), (109.00, -0.1187), (110.00, -0.1222)		
Policy_influence_on_coal	-0.04		
Population_change_energy	Population_change_rate*Population_Influence_Coefficient		
Population_change_rate	(Population.Population-DELAY(Population.Population, 1))/DELAY(Population.Population, 1)		
Population_Influence_Coefficient	1.2		
"Proportion_of_non-fossil_energy"	(Primary_electricity_consumption+Net_Input_of_Electricity)/Total_energy_consumption		
Ratio_coefficient_of_coal	0.720*EXP(-0.022*(TIME-1))*SIN(0.594*(TIME-1)+0.944)+0.514		

Ratio_coefficient_of_Electricity	-0.991 * EXP(-0.898 * (TIME - 1)) * SIN(0.5 * (TIME - 1) + 0.172) + 2.199		
Ratio_coefficient_of_gas	18.033*EXP(-1.0*(TIME-1))*SIN(0.3*(TIME-1)+2.137)+2.794		
Ratio_coefficient_of_oil	-0.988 * EXP(-0.155 * (TIME - 1)) * SIN(0.5 * (TIME - 1) - 0.881) + 0.504		
Total_energy_consumption	Primary_electricity_consumption+Oil_energy_consumption+Coal_energy_consumption+Gas_energy_consumption+Net_Input_of_Electricity		
Carbon_storage:			
Carbon_storage	("Cultivated_land-carbon_storage"+"Forestland-carbon_storage" +"Grassland-carbon_storage"+"Land_use/_land_cover".Wetland*(20.75+13.6+160.42+2.65)+"Land_use/_land_cover".Construction_land*20.78+"Land_use/_land_cover".Barren_land*(1.82+15.88))		
"Cultivated_land-_above_ground"	7.74		
"Cultivated_land-_below_ground"	5.26		
"Cultivated_land-_death_organic_carbon"	1.32		
"Cultivated_land-_soil_organic_carbon"	57.83*(1+0.005*(Soil_conservation.Soil_Conservation_quantity-INIT(Soil_conservation.Soil_Conservation_quantity))/INIT(Soil_conservation.Soil_Conservation_quantity))		
"Cultivated_land-carbon_storage"	"Land_use/_land_cover".Cultivated_land*("Cultivated_land-_soil_organic_carbon"+"Cultivated_land-_death_organic_carbon"+"Cultivated_land-_below_ground"+"Cultivated_land-_above_ground")		
"Forestland-	28.38		

_above_ground"			
"Forestland-_below_ground"	10.82		
"Forestland-_death_organic_carbon"	2.15		
"Forestland-_soil_organic_carbon"	95.35*(1+0.003*(Soil_conservation.Soil_Conservation_quantity-INIT(Soil_conservation.Soil_Conservation_quantity))/INIT(Soil_conservation.Soil_Conservation_quantity))		
"Forestland-carbon_storage"	"Land_use/_land_cover".Forestland*("Forestland-_soil_organic_carbon"+"Forestland-_death_organic_carbon"+"Forestland-_below_ground"+"Forestland-_above_ground")		
"Grassland-_above_ground"	14.29		
"Grassland-_below_ground"	15.19		
"Grassland-_death_organic_carbon"	8.46		
"Grassland-_soil_organic_carbon"	75.7*(1+0.006*(Soil_conservation.Soil_Conservation_quantity-INIT(Soil_conservation.Soil_Conservation_quantity))/INIT(Soil_conservation.Soil_Conservation_quantity))		
"Grassland-carbon_storage"	"Land_use/_land_cover".Grassland*("Grassland-_soil_organic_carbon"+"Grassland-_death_organic_carbon"+"Grassland-_below_ground"+"Grassland-_above_ground")		
Climate_regulation:			

Climatic_factors	Precipitation_factor*Temperature_factor		
Precipitation	GRAPH(TIME) Points: (31.00, 622.0), (33.724137931, 636.6), (36.4482758621, 651.1), (39.1724137931, 665.7), (41.8965517241, 680.2), (44.6206896552, 694.8), (47.3448275862, 709.3), (50.0689655172, 723.9), (52.7931034483, 738.4), (55.5172413793, 753.0), (58.2413793103, 767.5), (60.9655172414, 782.1), (63.6896551724, 796.6), (66.4137931034, 811.2), (69.1379310345, 825.7), (71.8620689655, 840.3), (74.5862068966, 854.8), (77.3103448276, 869.4), (80.0344827586, 883.9), (82.7586206897, 898.5), (85.4827586207, 913.0), (88.2068965517, 927.6), (90.9310344828, 942.1), (93.6551724138, 956.7), (96.3793103448, 971.2), (99.1034482759, 985.8), (101.827586207, 1000.0), (104.551724138, 1015.0), (107.275862069, 1029.0), (110.00, 1044.0)		
Precipitation_factor	MAX(0.01, 1 - ((Precipitation - 700) / 300)^2)		
Temperature	GRAPH(TIME) Points: (31.00, 14.120), (33.724137931, 14.160), (36.4482758621, 14.200), (39.1724137931, 14.250), (41.8965517241, 14.290), (44.6206896552, 14.330), (47.3448275862, 14.370), (50.0689655172, 14.410), (52.7931034483, 14.460), (55.5172413793, 14.500), (58.2413793103, 14.540), (60.9655172414, 14.580), (63.6896551724, 14.620), (66.4137931034, 14.670), (69.1379310345, 14.710), (71.8620689655, 14.750), (74.5862068966, 14.790), (77.3103448276, 14.840), (80.0344827586, 14.880), (82.7586206897, 14.920), (85.4827586207, 14.960), (88.2068965517, 15.000), (90.9310344828, 15.050), (93.6551724138, 15.090), (96.3793103448, 15.130), (99.1034482759, 15.170), (101.827586207, 15.210), (104.551724138, 15.260), (107.275862069, 15.300), (110.00, 15.340)		
Temperature_factor	MAX(0.01, 1 - 0.1 * MAX(0, Temperature - 14.5)^2)		
Farming_production:			
Effect_of_CPI_on_irrigation	GRAPH(GDP."Consumer_price_index_(CPI)") Points: (1.000, 1.1100), (1.980, 1.0690), (2.960, 1.0280), (3.940, 0.9870), (4.920, 0.9460), (5.900, 0.9050), (6.880, 0.8640), (7.860, 0.8230), (8.840, 0.7820), (9.820, 0.7410), (10.800, 0.7000)		
Effect_of_irrigation_on_crop_yield	GRAPH(Irrigation) Points: (2723967118, 6.00), (2743864940.18, 6.134), (2763762762.36, 6.268), (2783660584.54, 6.40), (2803558406.72, 6.531), (2823456228.9, 6.662), (2843354051.08, 6.791),		

	(2863251873.26, 6.919), (2883149695.44, 7.046), (2903047517.62, 7.173), (2922945339.8, 7.298), (2942843161.97, 7.422), (2962740984.15, 7.546), (2982638806.33, 7.668), (3002536628.51, 7.79), (3022434450.69, 7.91), (3042332272.87, 8.03), (3062230095.05, 8.149), (3082127917.23, 8.266), (3102025739.41, 8.383), (3121923561.59, 8.499), (3141821383.77, 8.614), (3161719205.95, 8.728), (3181617028.13, 8.842), (3201514850.31, 8.954), (3221412672.49, 9.066), (3241310494.67, 9.176), (3261208316.85, 9.286), (3281106139.03, 9.395), (3301003961.21, 9.503), (3320901783.39, 9.611), (3340799605.57, 9.717), (3360697427.75, 9.823), (3380595249.92, 9.928), (3400493072.1, 10.03), (3420390894.28, 10.14), (3440288716.46, 10.24), (3460186538.64, 10.34), (3480084360.82, 10.44), (3499982183, 10.54), (3519880005.18, 10.64), (3539777827.36, 10.74), (3559675649.54, 10.84), (3579573471.72, 10.93), (3599471293.9, 11.03), (3619369116.08, 11.12), (3639266938.26, 11.22), (3659164760.44, 11.31), (3679062582.62, 11.41), (3698960404.8, 11.50), (3718858226.98, 11.59), (3738756049.16, 11.68), (3758653871.34, 11.77), (3778551693.52, 11.86), (3798449515.69, 11.95), (3818347337.87, 12.04), (3838245160.05, 12.13), (3858142982.23, 12.22), (3878040804.41, 12.30), (3897938626.59, 12.39), (3917836448.77, 12.47), (3937734270.95, 12.56), (3957632093.13, 12.64), (3977529915.31, 12.72), (3997427737.49, 12.81), (4017325559.67, 12.89), (4037223381.85, 12.97), (4057121204.03, 13.05), (4077019026.21, 13.13), (4096916848.39, 13.21), (4116814670.57, 13.29), (4136712492.75, 13.37), (4156610314.93, 13.44), (4176508137.11, 13.52), (4196405959.29, 13.60), (4216303781.47, 13.67), (4236201603.64, 13.75), (4256099425.82, 13.82), (4275997248, 13.90), (4295895070.18, 13.97), (4315792892.36, 14.04), (4335690714.54, 14.11), (4355588536.72, 14.19), (4375486358.9, 14.26), (4395384181.08, 14.33), (4415282003.26, 14.40), (4435179825.44, 14.47), (4455077647.62, 14.54), (4474975469.8, 14.60), (4494873291.98, 14.67), (4514771114.16, 14.74), (4534668936.34, 14.81), (4554566758.52, 14.87), (4574464580.7, 14.94), (4594362402.88, 15.00), (4614260225.06, 15.07), (4634158047.24, 15.13), (4654055869.41, 15.20), (4673953691.59, 15.26), (4693851513.77, 15.32), (4713749335.95, 15.39), (4733647158.13, 15.45), (4753544980.31, 15.51), (4773442802.49, 15.57), (4793340624.67, 15.63), (4813238446.85, 15.69), (4833136269.03, 15.75),		

	(4853034091.21, 15.81), (4872931913.39, 15.87), (4892829735.57, 15.93), (4912727557.75, 15.98), (4932625379.93, 16.04), (4952523202.11, 16.10), (4972421024.29, 16.15), (4992318846.47, 16.21), (5012216668.65, 16.27), (5032114490.83, 16.32), (5052012313.01, 16.38), (5071910135.19, 16.43), (5091807957.36, 16.48), (5111705779.54, 16.54), (5131603601.72, 16.59), (5151501423.9, 16.64), (5171399246.08, 16.70), (5191297068.26, 16.75), (5211194890.44, 16.80), (5231092712.62, 16.85), (5250990534.8, 16.90), (5270888356.98, 16.95), (5290786179.16, 17.00)		
Effect_of_rainfall_on_crop_yield	GRAPH(Climate_regulation.Precipitation) Points: (0, 0.00), (71.4757142857, 0.24), (142.951428571, 0.48), (214.427142857, 0.81), (285.902857143, 1.13), (357.378571429, 2.46), (428.854285714, 3.69), (500.33, 4.77), (571.805714286, 6.54), (643.281428571, 8.72), (714.757142857, 13.64), (786.232857143, 17.35), (857.708571429, 18.00), (929.184285714, 15.74), (1000.66, 10.41)		
Effect_of_Rainfall_on_irrigation	GRAPH(Climate_regulation.Precipitation) Points: (713.0, 1.15), (723.7, 1.14), (734.4, 1.13), (745.1, 1.12), (755.8, 1.11), (766.5, 1.1), (777.2, 1.09), (787.9, 1.08), (798.6, 1.07), (809.3, 1.06), (820.0, 1.05)		
Effect_of_soil_conservation_quality_on_crop_yield	GRAPH(Soil_conservation.Soil_Conservation_quantity) Points: (207.1767859, 8.000), (223.651166743, 8.872), (240.125547586, 9.685), (256.599928429, 10.440), (273.074309271, 11.150), (289.548690114, 11.800), (306.023070957, 12.410), (322.4974518, 12.980), (338.971832643, 13.510), (355.446213486, 14.000), (371.920594329, 14.460), (388.394975171, 14.890), (404.869356014, 15.290), (421.343736857, 15.660), (437.8181177, 16.000)		
Effect_of_subsidy_on_irrigation_withdrawal	GRAPH(Farming_subsidy) Points: (137481875.47, 0.000), (731399866.595, 0.004149), (1325317857.72, 0.009726), (1919235848.85, 0.01729), (2513153839.97, 0.02759), (3107071831.1, 0.04163), (3700989822.22, 0.06073), (4294907813.35, 0.08654), (4888825804.47, 0.121), (5482743795.6, 0.1663), (6076661786.72, 0.2246), (6670579777.85, 0.2972), (7264497768.97, 0.3845), (7858415760.1, 0.4846), (8452333751.22, 0.5938), (9046251742.35, 0.7062), (9640169733.47, 0.8154), (10234087724.6, 0.9155), (10828005715.7, 1.003), (11421923706.8, 1.075), (12015841698, 1.134), (12609759689.1, 1.179), (13203677680.2, 1.213), (13797595671.3, 1.239), (14391513662.5, 1.258), (14985431653.6, 1.272), (15579349644.7, 1.283),		

	(16173267635.8, 1.290), (16767185627, 1.296), (17361103618.1, 1.300)		
Effect_of_technology_on_crop_yield	GRAPH(MIN(technology_support, 1)) Points: (0.000, 2.00), (0.0344827586207, 3.832), (0.0689655172414, 5.488), (0.103448275862, 6.984), (0.137931034483, 8.336), (0.172413793103, 9.557), (0.206896551724, 10.66), (0.241379310345, 11.66), (0.275862068966, 12.56), (0.310344827586, 13.37), (0.344827586207, 14.11), (0.379310344828, 14.77), (0.413793103448, 15.37), (0.448275862069, 15.92), (0.48275862069, 16.41), (0.51724137931, 16.85), (0.551724137931, 17.25), (0.586206896552, 17.61), (0.620689655172, 17.94), (0.655172413793, 18.24), (0.689655172414, 18.50), (0.724137931034, 18.74), (0.758620689655, 18.96), (0.793103448276, 19.16), (0.827586206897, 19.34), (0.862068965517, 19.50), (0.896551724138, 19.64), (0.931034482759, 19.77), (0.965517241379, 19.89), (1.000, 20.00)		
Effect_of_temperature_on_crop_yield	GRAPH(Climate_regulation.Temperature) Points: (13.300, 3.00), (13.5473684211, 11.65), (13.7947368421, 14.41), (14.0421052632, 14.93), (14.2894736842, 17.24), (14.5368421053, 18.21), (14.7842105263, 17.91), (15.0315789474, 16.1223591616), (15.2789473684, 14.8178854512), (15.5263157895, 12.62), (15.7736842105, 10.61), (16.0210526316, 9.49), (16.2684210526, 8.67), (16.5157894737, 7.18), (16.7631578947, 6.65), (17.0105263158, 5.91), (17.2578947368, 5.16), (17.5052631579, 4.57), (17.7526315789, 3.67), (18.000, 3.00)		
Farming_investment	0.1207*Primary_industry_investment^ 1.076870		
Farming_production	"Land_use/_land_cover".Cultivated_land*Yield		
Farming_subsidy	Farming_investment*0.2		
Irragation_change_rate	MIN(0.45+(0.007*TIME), 0.9)		
Irrigated_land	"Land_use/_land_cover".Cultivated_land*Irragation_change_rate		
Irrigation	Irrigated_land*"Irrigation_water/ha"*(Effect_of_subsidy_on_irrigation_withdrawal*0.333+Effect_of_Rainfall_on_irrigation*0.333+Effect_of_CPI_on_irrigation*0.333)		
"Irrigation_water/ha"	GRAPH(TIME) Points: (1.00, 653.0), (3.90, 683.0), (6.80, 713.0), (9.70, 743.0), (12.60, 773.0), (15.50, 803.0), (18.40,		

	833.0), (21.30, 863.0), (24.20, 893.0), (27.10, 923.0), (30.00, 953.0)		
Primary_industry_investment	0.0000001815*GDP.Primary_GDP^1.474176		
technology_support	GRAPH(GDP.GDP) Points: (181054000000, 0.000), (757950168690, 0.05362), (1334846337380, 0.1054), (1911742506070, 0.1555), (2488638674760, 0.2038), (3065534843450, 0.2505), (3642431012140, 0.2957), (4219327180830, 0.3393), (4796223349520, 0.3814), (5373119518210, 0.4221), (5950015686900, 0.4614), (6526911855590, 0.4994), (7103808024280, 0.5361), (7680704192970, 0.5715), (8257600361660, 0.6058), (8834496530340, 0.6389), (9411392699030, 0.6708), (9988288867720, 0.7017), (10565185036400, 0.7315), (11142081205100, 0.7604), (11718977373800, 0.7882), (12295873542500, 0.8151), (12872769711200, 0.8411), (13449665879900, 0.8662), (14026562048600, 0.8905), (14603458217200, 0.9139), (15180354385900, 0.9366), (15757250554600, 0.9584), (16334146723300, 0.9796), (16911042892000, 1.000)		
Yield	MAX(3, Effect_of_technology_on_crop_yield)*0.4+Effect_of_rainfall_on_crop_yield*0.1+MAX(0, Effect_of_temperature_on_crop_yield)*0.3+Effect_of_soil_conservation_quality_on_crop_yield*0.1+Effect_of_irrigation_on_crop_yield*0.1		
GDP:			
GDP(t)	GDP(t - dt) + (GDP_inflow - GDP_outflow) * dt	INIT GDP = 630121000000	
Primary_GDP(t)	Primary_GDP(t - dt) + ("1st_GDP_inflow" - "2nd_GDP_outflow") * dt	INIT Primary_GDP = 536435000000	
"1st_GDP_inflow"	Price_change_considered_1st_production-Primary_GDP		
"2nd_GDP_outflow"	Primary_GDP-Price_change_considered_1st_production		

GDP_inflow	Indicated_GDP-GDP		
GDP_outflow	GDP-Indicated_GDP		
"3rd_GDP"	Effect_of_urbanization_rate_on_3rd_GDP*0.25+Effect_of_urban_land_on_3rd_GDP*0.25+Effect_of_tourism_on_3rd_GDP*0.25+Effect_of_CPI_on_3rd_GDP*0.25		
"Consumer_price_index_(CPI)"	GRAPH(TIME) Points: (1.00, 1.000), (2.00, 1.076), (3.00, 1.152), (4.00, 1.228), (5.00, 1.303), (6.00, 1.379), (7.00, 1.455), (8.00, 1.531), (9.00, 1.607), (10.00, 1.683), (11.00, 1.759), (12.00, 1.834), (13.00, 1.910), (14.00, 1.986), (15.00, 2.062), (16.00, 2.138), (17.00, 2.214), (18.00, 2.290), (19.00, 2.366), (20.00, 2.441), (21.00, 2.517), (22.00, 2.593), (23.00, 2.669), (24.00, 2.745), (25.00, 2.821), (26.00, 2.897), (27.00, 2.972), (28.00, 3.048), (29.00, 3.124), (30.00, 3.200)		
Effect_of_available_water_on_2nd_GDP	GRAPH(Water_yield.Water_Yield) Points: (98.00, 1.09e+12), (111.00, 1.26e+12), (112.00, 1.26e+12), (113.00, 1.27e+12), (114.00, 1.3e+12), (117.00, 1.36e+12), (118.00, 1.36e+12), (118.00, 1.36e+12), (119.00, 1.39e+12), (120.00, 1.46e+12), (127.00, 1.54e+12), (128.00, 1.57e+12), (131.00, 1.64e+12), (131.00, 1.64e+12), (131.00, 1.64e+12), (131.00, 1.64e+12), (135.00, 1.71e+12), (137.00, 1.71e+12), (137.00, 1.71e+12), (138.00, 1.73e+12), (140.00, 1.78e+12), (141.00, 1.82e+12), (145.00, 1.87e+12), (145.00, 1.87e+12), (147.00, 1.96e+12), (156.00, 2.06e+12), (158.00, 2.11e+12), (178.00, 2.36e+12), (181.00, 2.56e+12), (193.00, 2.81e+12)		
Effect_of_construction_land_on_2nd_GDP	GRAPH("Land_use/_land_cover".Construction_land) Points: (1789279, 74590000000), (1844238, 99911000000), (1916851, 135571000000), (1963307, 189143000000), (2007863, 235578000000), (2049865, 278409000000), (2112594, 314737000000), (2157833, 340806000000), (2214113, 364432000000), (2272269, 412019000000), (2304486, 446674000000), (2341818, 503763000000), (2395651, 572001000000), (2446364, 732761000000), (2499042, 884113000000), (2554350, 1056849000000), (2639285, 1252941000000), (2697741, 1491150000000), (2752636, 1591967000000), (2800194, 1773308000000), (2865766, 1992611000000), (2924897, 2127589000000), (3026200, 2261589000000), (3068436, 2358802000000), (3127499, 2481488000000), (3172624, 2.55e+12), (3213678, 2.57e+12), (3258131, 2.62e+12), (3296734, 2.68e+12), (3452989, 2845666000000)		

Effect_of_CPI_on_2nd_GDP	GRAPH("Consumer_price_index_(CPI)") Points: (1.000, 74590000000), (1.07586206897, 99911000000), (1.15172413793, 135571000000), (1.2275862069, 189143000000), (1.30344827586, 235578000000), (1.37931034483, 278409000000), (1.45517241379, 314737000000), (1.53103448276, 340806000000), (1.60689655172, 364432000000), (1.68275862069, 412019000000), (1.75862068966, 446674000000), (1.83448275862, 503763000000), (1.91034482759, 572001000000), (1.98620689655, 732761000000), (2.06206896552, 884113000000), (2.13793103448, 1056849000000), (2.21379310345, 1252941000000), (2.28965517241, 1491150000000), (2.36551724138, 1591967000000), (2.44137931034, 1773308000000), (2.51724137931, 1992611000000), (2.59310344828, 2127589000000), (2.66896551724, 2261589000000), (2.74482758621, 2358802000000), (2.82068965517, 2481488000000), (2.89655172414, 2556504000000), (2.9724137931, 2817178000000), (3.04827586207, 2692559000000), (3.12413793103, 2752367000000), (3.200, 2845666000000)		
Effect_of_CPI_on_3rd_GDP	GRAPH("Consumer_price_index_(CPI)") Points: (1.000, 54279000000), (1.07586206897, 66280000000), (1.15172413793, 81803000000), (1.2275862069, 117804000000), (1.30344827586, 158744000000), (1.37931034483, 189954000000), (1.45517241379, 219470000000), (1.53103448276, 239749000000), (1.60689655172, 262852000000), (1.68275862069, 290579000000), (1.75862068966, 326902000000), (1.83448275862, 366974000000), (1.91034482759, 372624000000), (1.98620689655, 423225000000), (2.06206896552, 517821000000), (2.13793103448, 630105000000), (2.21379310345, 773764000000), (2.28965517241, 931852000000), (2.36551724138, 1054494000000), (2.44137931034, 1277807000000), (2.51724137931, 1537027000000), (2.59310344828, 1763436000000), (2.66896551724, 2027433000000), (2.74482758621, 2252401000000), (2.82068965517, 2557109000000), (2.89655172414, 2836717000000), (2.9724137931, 3125380000000), (3.04827586207, 3417468000000), (3.12413793103, 3725171000000), (3.200, 3897716000000)		
Effect_of_energy_consumption_on_2nd_GDP	GRAPH(Carbon_emission.Total_energy_consumption) Points: (108830209.3, 74590000000), (124438404.6, 99911000000), (231134276.1, 135571000000), (271052467.7, 189143000000), (302259119, 235578000000), (322475605.2, 278409000000), (334191588.5, 314737000000), (344099440.8, 340806000000), (355762065.4, 364432000000),		

	(376002563.6, 412019000000), (390261869.3, 446674000000), (417675446.1, 503763000000), (450707785.1, 572001000000), (484606692.4, 732761000000), (525876260.6, 884113000000), (564144096.9, 1056849000000), (598146293.2, 1252941000000), (625152081.4, 1491150000000), (658148959.1, 1591967000000), (692700444.9, 1773308000000), (711419308.6, 1992611000000), (728575718.8, 2127589000000), (758227654.8, 2261589000000), (797081745.4, 2.52e+12), (824005120.6, 2.68e+12), (826623497, 2.68e+12), (838398487.2, 2.75e+12), (847927730.5, 2.83e+12), (848018056.3, 2.85e+12), (851301681, 2.85e+12)		
Effect_of_tourism_on_3rd_GDP	GRAPH(Aesthetic_landscape.Aesthetic_landscape) Points: (6548400091, 0), (6618361800.31, 79580000000), (6688323509.62, 162000000000), (6758285218.93, 247200000000), (6828246928.24, 335500000000), (6898208637.55, 426800000000), (6968170346.86, 521400000000), (7038132056.17, 619300000000), (7108093765.48, 720600000000), (7178055474.79, 825500000000), (7248017184.1, 934000000000), (7317978893.41, 1046000000000), (7387940602.72, 1163000000000), (7457902312.03, 1283000000000), (7527864021.34, 1408000000000), (7597825730.66, 1537000000000), (7667787439.97, 1.67e+12), (7737749149.28, 1808000000000), (7807710858.59, 1951000000000), (7877672567.9, 2099000000000), (7947634277.21, 2253000000000), (8017595986.52, 2411000000000), (8087557695.83, 2575000000000), (8157519405.14, 2745000000000), (8227481114.45, 2921000000000), (8297442823.76, 3103000000000), (8367404533.07, 3292000000000), (8437366242.38, 3487000000000), (8507327951.69, 3689000000000), (8577289661, 3898000000000)		
Effect_of_urban_land_on_3rd_GDP	GRAPH(Population.Urban_land_demand) Points: (995344, 54279000000), (1036602, 66280000000), (1082367, 81803000000), (1130037, 117804000000), (1178899, 158744000000), (1227460, 189954000000), (1275226, 219470000000), (1323036, 239749000000), (1371799, 262852000000), (1422068, 290579000000), (1474212, 326902000000), (1528624, 366974000000), (1585735, 372624000000), (1645920, 423225000000), (1709277, 517821000000), (1775625, 630105000000), (1844612, 773764000000), (1915725, 931852000000), (1988421, 1054494000000), (2062376, 1277807000000), (2137117, 1537027000000), (2211984, 1763436000000), (2286460, 2027433000000), (2360297, 2252401000000), (2433309, 2557109000000), (2509316, 2836717000000), (2585427,		

	3125380000000), (2660159, 3417468000000), (2733328, 3725171000000), (2804918, 3897716000000)		
Effect_of_urbanization_rate_on_3rd_GDP	GRAPH(Urbanization_rate) Points: (0.2000, 54279000000), (0.2100, 66280000000), (0.2200, 81803000000), (0.2300, 117804000000), (0.2400, 158744000000), (0.2400, 189954000000), (0.2500, 219470000000), (0.2600, 239749000000), (0.2700, 262852000000), (0.2800, 290579000000), (0.2900, 326902000000), (0.3000, 366974000000), (0.3100, 372624000000), (0.3200, 423225000000), (0.3300, 517821000000), (0.3400, 630105000000), (0.3500, 773764000000), (0.3600, 931852000000), (0.3700, 1054494000000), (0.3800, 1277807000000), (0.4000, 1537027000000), (0.4100, 1763436000000), (0.4200, 2027433000000), (0.4300, 2252401000000), (0.4400, 2557109000000), (0.4600, 2836717000000), (0.4700, 3125380000000), (0.4800, 3417468000000), (0.4900, 3725171000000), (0.5100, 3897716000000)		
Indicated_GDP	Secondary_GDP+"3rd_GDP"+Primary_GDP		
Price_change_considered_1st_production	Primary_industry_production*"Consumer_price_index_(CPI)"*1034		
Primary_industry_production	Aquatic_production.Aquatic_production+Farming_production.Farming_production		
Secondary_GDP	Effect_of_available_water_on_2nd_GDP*0.25+Effect_of_construction_land_on_2nd_GDP*0.25+Effect_of_CPI_on_2nd_GDP*0.25+Effect_of_energy_consumption_on_2nd_GDP*0.25		
Urbanization_rate	MIN(0.0001008*TIME*TIME+0.00732*TIME+0.1972, 0.80)		
"Land_use/_land_cover":			
Barren_land(t)	Barren_land(t - dt) + (Flow_of_barren_and_grassland - Flow_of_barren_and_water_cover - Flow_of_construction_and_barren_land - "Barren-farmland_change") * dt	INIT Barren_land = 40365	ha
Construction_land(t)	Construction_land(t - dt) + (Flow_of_construction_and_grassland + Flow_of_construction_and_barren_land + Urban_expansion_from_farmland) * dt	INIT Construction_land =	ha

		3452989	
Cultivated_land(t)	Cultivated_land(t - dt) + ("Barren-farmland_change" + "Grassland-cultivated_change_rate" - Flow_of_cultivated_land_and_forestland - Urban_expansion_from_farmland - Flow_of_cultivated_land_and_water_cover) * dt	INIT Cultivated_land = 10631598	ha
Forestland(t)	Forestland(t - dt) + (Flow_of_cultivated_land_and_forestland + Flow_of_shrub_land_and_forest) * dt	INIT Forestland = 782325	ha
Grassland(t)	Grassland(t - dt) + (Flow_of_shrub_and_grassland - Flow_of_construction_and_grassland - "Grassland-cultivated_change_rate" - Flow_of_barren_and_grassland) * dt	INIT Grassland = 214035	ha
Shrub_land(t)	Shrub_land(t - dt) + (- Flow_of_shrub_and_grassland - Flow_of_shrub_land_and_forest) * dt	INIT Shrub_land = 32	ha
Water_covered_land(t)	Water_covered_land(t - dt) + (Flow_of_barren_and_water_cover + Water_expansion_from_wetland + Flow_of_cultivated_land_and_water_cover) * dt	INIT Water_covered_land = 362359	ha
Wetland(t)	Wetland(t - dt) + (- Water_expansion_from_wetland) * dt	INIT Wetland = 0.001	ha
"Barren-farmland_change"	IF Climate_regulation.Climatic_factors>0.05 THEN (IF Cultivated_land-Population.Farming_land_demand>0 THEN -(Cultivated_land-Population.Farming_land_demand)/50 ELSE 0) ELSE(IF Cultivated_land-Population.Farming_land_demand>0 THEN -(Cultivated_land)*(1-Climate_regulation.Climatic_factors)/10 ELSE 0)	OUTFLOW PRIORITY: 4	ha/Months
Flow_of_barren_and_grassland	IF Climate_regulation.Climatic_factors>0.1 THEN 0 ELSE(Grassland)*(1-Climate_regulation.Climatic_factors)/10	OUTFLOW	ha/M

		PRIORITY: 4	onths
Flow_of_barren_and_water_cover	Water_balance.Water_flow/"barren-water_transfer_year"	OUTFLOW PRIORITY: 1	ha/Months
Flow_of_construction_and_barren_land	IF Population.Construction_demand> Construction_land THEN (Population.Construction_demand-Construction_land)/"Barren-urban_transfer_year" ELSE -(Construction_land-Population.Construction_demand)/15	OUTFLOW PRIORITY: 2	ha/Months
Flow_of_construction_and_grassland	IF Population.Construction_demand-Construction_land>0 THEN 0.024*Grassland ELSE (((DELAY1(Construction_land, 1)-Construction_land))/Grassland_transfer_year)*Climate_regulation.Climatic_factors	OUTFLOW PRIORITY: 2	ha/Months
Flow_of_cultivated_land_and_forestland	MAX(IF Cultivated_land-Population.Farming_land_demand>0 THEN (IF TIME >14 THEN (DELAY1(0.00001053*Carbon_emission.Carbon_dioxide_emission, 20) +(Aesthetic_landscape.Aesthetic_landscape-DELAY(Aesthetic_landscape.Aesthetic_landscape, 1))/Aesthetic_landscape.Aesthetic_landscape*Forestland/30 +(Cultivated_land-Population.Farming_land_demand)*(Climate_regulation.Climatic_factors)/50) ELSE +(Cultivated_land-Population.Farming_land_demand)*(Climate_regulation.Climatic_factors)/100) ELSE -Forestland/10, 0)	OUTFLOW PRIORITY: 1	ha/Months
Flow_of_cultivated_land_and_water_cover	IF Cultivated_land-Population.Farming_land_demand>0 THEN (0.05*(Water_balance.Water_flow)) +((Aesthetic_landscape.Aesthetic_landscape-DELAY(Aesthetic_landscape.Aesthetic_landscape, 1))/Aesthetic_landscape.Aesthetic_landscape)*Water_covered_land/10 ELSE 0	OUTFLOW PRIORITY: 3	ha/Months
Flow_of_shrub_and_grassland	IF Climate_regulation.Climatic_factors>0.2 THEN 0 ELSE (Shrub_land)*(1-Climate_regulation.Climatic_factors)/20	OUTFLOW PRIORITY: 1	ha/Months

Flow_of_shrub_land_and_forest	IF Climate_regulation.Climatic_factors>0.35 THEN 0.074*Shrub_land*(1-Climate_regulation.Climatic_factors) ELSE -(Forestland)/100	OUTFLOW PRIORITY: 2	ha/Months
"Grassland-cultivated_change_rate"	IF Cultivated_land-Population.Farming_land_demand>0 THEN -(Grassland-DELAY(Grassland, 1))/10-(Aesthetic_landscape.Aesthetic_landscape-DELAY(Aesthetic_landscape.Aesthetic_landscape, 1))/Aesthetic_landscape.Aesthetic_landscape*Grassland/5 ELSE 0	OUTFLOW PRIORITY: 3	ha/Months
Urban_expansion_from_farmland	IF Population.Construction_demand-Construction_land>0 THEN (Population.Construction_demand-Construction_land)/5 ELSE 0	OUTFLOW PRIORITY: 2	ha/Months
Water_expansion_from_wetland	IF TIME <20 THEN 0.252*Wetland ELSE -0.052*Wetland +((Aesthetic_landscape.Aesthetic_landscape-DELAY(Aesthetic_landscape.Aesthetic_landscape, 1))/Aesthetic_landscape.Aesthetic_landscape)*Wetland/20		ha/Months
"Barren-urban_transfer_year"	GRAPH(TIME) Points: (1.00, 25.00), (2.00, 24.28), (3.00, 23.55), (4.00, 22.83), (5.00, 22.10), (6.00, 21.38), (7.00, 20.66), (8.00, 19.93), (9.00, 19.21), (10.00, 18.48), (11.00, 17.76), (12.00, 17.03), (13.00, 16.31), (14.00, 15.59), (15.00, 14.86), (16.00, 14.14), (17.00, 13.41), (18.00, 12.69), (19.00, 11.97), (20.00, 11.24), (21.00, 10.52), (22.00, 9.793), (23.00, 9.069), (24.00, 8.345), (25.00, 7.621), (26.00, 6.897), (27.00, 6.172), (28.00, 5.448), (29.00, 4.724), (30.00, 4.00)		
"barren-water_transfer_year"	30		
Grassland_transfer_year	30		
Population:			
"Aged_1-15"(t)	"Aged_1-15"(t - dt) + (Births - "Aging_Flow_0-14_to_15-64") * dt	INIT "Aged_1-15" = 19103016	

"Aged_15-64"(t)	"Aged_15-64"(t - dt) + ("Aging_Flow_0-14_to_15-64" - "Aging_Flow_15-64_to_65") * dt	INIT "Aged_15-64" = 67226748	
Aged_65(t)	Aged_65(t - dt) + ("Aging_Flow_15-64_to_65" - Deaths) * dt	INIT Aged_65 = 15390236	
"Aging_Flow_0-14_to_15-64"	DELAYN(Births,"Age_Span_0-14",10,1519746*(1-"Death_rate_0-14"))		
"Aging_Flow_15-64_to_65"	DELAYN("Aging_Flow_0-14_to_15-64","Age_Span_15-64",10,57348480/55*(1-"Death_rate_15-64"))		
Births	"Aged_15-64"*0.45*Fraction_women*(Observed_fertility/Fertile_period_year)		
Deaths	DELAYN("Aging_Flow_15-64_to_65",Age_Span_64_to_die,10,5313400/10)		
"2nd_child_Policy_impact"	GRAPH(Higher_education_rate) Points: (-0.002514995, 0.7000), (0.00827633405063, 0.6901), (0.0190676631013, 0.6802), (0.0298589921519, 0.6705), (0.0406503212025, 0.6609), (0.0514416502532, 0.6515), (0.0622329793038, 0.6421), (0.0730243083544, 0.6329), (0.0838156374051, 0.6238), (0.0946069664557, 0.6148), (0.105398295506, 0.6060), (0.116189624557, 0.5972), (0.126980953608, 0.5885), (0.137772282658, 0.5800), (0.148563611709, 0.5715), (0.159354940759, 0.5632), (0.17014626981, 0.5550), (0.180937598861, 0.5469), (0.191728927911, 0.5388), (0.202520256962, 0.5309), (0.213311586013, 0.5231), (0.224102915063, 0.5154), (0.234894244114, 0.5077), (0.245685573165, 0.5002), (0.256476902215, 0.4928), (0.267268231266, 0.4854), (0.278059560316, 0.4782), (0.288850889367, 0.4710), (0.299642218418, 0.4639), (0.310433547468, 0.4570), (0.321224876519, 0.4501), (0.33201620557, 0.4433), (0.34280753462, 0.4365), (0.353598863671, 0.4299), (0.364390192722, 0.4234), (0.375181521772, 0.4169), (0.385972850823, 0.4105), (0.396764179873, 0.4042), (0.407555508924, 0.3980), (0.418346837975, 0.3918), (0.429138167025, 0.3857), (0.439929496076, 0.3797), (0.450720825127, 0.3738), (0.461512154177, 0.3680), (0.472303483228, 0.3622), (0.483094812278, 0.3565), (0.493886141329,		

	0.3509), (0.50467747038, 0.3453), (0.51546879943, 0.3398), (0.526260128481, 0.3344), (0.537051457532, 0.3291), (0.547842786582, 0.3238), (0.558634115633, 0.3186), (0.569425444684, 0.3134), (0.580216773734, 0.3083), (0.591008102785, 0.3033), (0.601799431835, 0.2983), (0.612590760886, 0.2934), (0.623382089937, 0.2886), (0.634173418987, 0.2838), (0.644964748038, 0.2791), (0.655756077089, 0.2745), (0.666547406139, 0.2699), (0.67733873519, 0.2653), (0.688130064241, 0.2608), (0.698921393291, 0.2564), (0.709712722342, 0.2520), (0.720504051392, 0.2477), (0.731295380443, 0.2435), (0.742086709494, 0.2393), (0.752878038544, 0.2351), (0.763669367595, 0.2310), (0.774460696646, 0.2270), (0.785252025696, 0.2230), (0.796043354747, 0.2190), (0.806834683797, 0.2151), (0.817626012848, 0.2113), (0.828417341899, 0.2075), (0.839208670949, 0.2037), (0.8500, 0.2000)		
"Age_Span_0-14"	15		
"Age_Span_15-64"	50		
Age_Span_64_to_die	GRAPH(TIME) Points: (1.00, 5.00), (2.00, 5.002), (3.00, 5.006), (4.00, 5.012), (5.00, 5.023), (6.00, 5.043), (7.00, 5.077), (8.00, 5.137), (9.00, 5.241), (10.00, 5.418), (11.00, 5.717), (12.00, 6.20), (13.00, 6.942), (14.00, 7.987), (15.00, 9.293), (16.00, 10.71), (17.00, 12.01), (18.00, 13.06), (19.00, 13.80), (20.00, 14.28), (21.00, 14.58), (22.00, 14.76), (23.00, 14.86), (24.00, 14.92), (25.00, 14.96), (26.00, 14.98), (27.00, 14.99), (28.00, 14.99), (29.00, 15.00), (30.00, 15.00)		
Birth_rate	Births/Population*1000		
Construction_demand	Rural_construction_demand+Urban_land_demand		
"Death_rate_0-14"	(1/1000) * (1 - Medical_Improvement_Factor)		
"Death_rate_15-64"	(5/1000) * (1 - Medical_Improvement_Factor)		
"Desired_Number_of_Children_(DNC)"	MAX(((DNC_1990 + (DNCmin - DNC_1990) * EXP(-DNCgamma * ("GDP/population_1991" - "GDP/population_1990"))) * (1 + GDP_impact * ("GDP/population_1991" - "GDP/population_1990"))) * (1 - Education_impact * Higher_education_rate) * (1 + "2nd_child_Policy_impact" * (TIME > 25)), 0.8)		1

DNC_1990	2		
DNCgamma	0.005		
DNCmin	1.4		
Education_impact	GRAPH(Higher_education_rate) Points: (-0.002514995, 0.0000), (0.00827633405063, 0.0005329), (0.0190676631013, 0.001125), (0.0298589921519, 0.001785), (0.0406503212025, 0.00252), (0.0514416502532, 0.003342), (0.0622329793038, 0.00426), (0.0730243083544, 0.005287), (0.0838156374051, 0.006437), (0.0946069664557, 0.007725), (0.105398295506, 0.009168), (0.116189624557, 0.01079), (0.126980953608, 0.0126), (0.137772282658, 0.01463), (0.148563611709, 0.01691), (0.159354940759, 0.01945), (0.17014626981, 0.0223), (0.180937598861, 0.02548), (0.191728927911, 0.02904), (0.202520256962, 0.0330), (0.213311586013, 0.0374), (0.224102915063, 0.04229), (0.234894244114, 0.04771), (0.245685573165, 0.05371), (0.256476902215, 0.06031), (0.267268231266, 0.06757), (0.278059560316, 0.07551), (0.288850889367, 0.08418), (0.299642218418, 0.09359), (0.310433547468, 0.1038), (0.321224876519, 0.1147), (0.33201620557, 0.1264), (0.34280753462, 0.1389), (0.353598863671, 0.1520), (0.364390192722, 0.1659), (0.375181521772, 0.1803), (0.385972850823, 0.1952), (0.396764179873, 0.2106), (0.407555508924, 0.2262), (0.418346837975, 0.2420), (0.429138167025, 0.2580), (0.439929496076, 0.2738), (0.450720825127, 0.2894), (0.461512154177, 0.3048), (0.472303483228, 0.3197), (0.483094812278, 0.3341), (0.493886141329, 0.3480), (0.50467747038, 0.3611), (0.51546879943, 0.3736), (0.526260128481, 0.3853), (0.537051457532, 0.3962), (0.547842786582, 0.4064), (0.558634115633, 0.4158), (0.569425444684, 0.4245), (0.580216773734, 0.4324), (0.591008102785, 0.4397), (0.601799431835, 0.4463), (0.612590760886, 0.4523), (0.623382089937, 0.4577), (0.634173418987, 0.4626), (0.644964748038, 0.4670), (0.655756077089, 0.4710), (0.666547406139, 0.4745), (0.67733873519, 0.4777), (0.688130064241, 0.4805), (0.698921393291, 0.4831), (0.709712722342, 0.4854), (0.720504051392, 0.4874), (0.731295380443, 0.4892), (0.742086709494, 0.4908), (0.752878038544, 0.4923), (0.763669367595, 0.4936), (0.774460696646, 0.4947), (0.785252025696, 0.4957), (0.796043354747, 0.4967), (0.806834683797, 0.4975), (0.817626012848, 0.4982), (0.828417341899, 0.4989), (0.839208670949, 0.4995), (0.8500, 0.5000)		

Farming_labor	Rural_population*0.74		
Farming_land_demand	MAX(Farming_labor*(0.23+0.0006*(TIME)),Minimum_demand_for_farmland)		ha
Fertile_period_year	20		y
Fraction_achieving_desired_family_size	0.9		1
Fraction_women	0.49		
GDP_impact	GRAPH("GDP/population_1991") Points: (2112.648775, 0), (3956.24906862, -4.29e-7), (5799.84936224, -0.0000013), (7643.44965586, -0.00000147), (9487.04994948, -0.00000182), (11330.6502431, -0.00000211), (13174.2505367, -0.00000232), (15017.8508303, -0.000002475), (16861.451124, -0.00000263), (18705.0514176, -0.00000281), (20548.6517112, -0.00000293), (22392.2520048, -0.00000305), (24235.8522984, -0.000003165), (26079.4525921, -0.00000328), (27923.0528857, -0.000003395), (29766.6531793, -0.00000351), (31610.2534729, -0.00000363), (33453.8537666, -0.00000375), (35297.4540602, -0.000003828), (37141.0543538, -0.000003906), (38984.6546474, -0.000003984), (40828.254941, -0.000004062), (42671.8552347, -0.00000414), (44515.4555283, -0.000004265), (46359.0558219, -0.00000439), (48202.6561155, -0.00000449), (50046.2564091, -0.00000456), (51889.8567028, -0.00000463), (53733.4569964, -0.00000467), (55577.05729, -0.00000488)		
"GDP/population_1990"	2122		
"GDP/population_1991"	GDP.GDP/Population		
Higher_education	GRAPH("GDP/population_1991") Points: (3517.860141, 1263032.000), (3783.744297, 1542796.000), (4101.574612, 1882491.000), (4479.856057, 2294696.000), (4929.699631, 2793803.000), (5464.985379, 3396078.000), (6102.544049, 4119709.000), (6858.73453, 4987472.000), (7755.204185, 6023317.000), (8820.845129, 7250273.000), (10086.14951,		

	8694408.000), (11589.47402, 10379365.000), (13377.05542, 12325163.000), (15498.03143, 14551738.000), (18011.88757, 17071064.000)		
Higher_education_rate	"Maximum-_Education_population"/Population		
"Maximum-_Education_population"	MIN(Higher_education, 0.85*Population)		
Medical_Improvement_Factor	GRAPH(TIME) Points: (1.00, 0.005), (2.00, 0.005316), (3.00, 0.005633), (4.00, 0.005949), (5.00, 0.006266), (6.00, 0.006582), (7.00, 0.006899), (8.00, 0.007215), (9.00, 0.007532), (10.00, 0.007848), (11.00, 0.008165), (12.00, 0.008481), (13.00, 0.008797), (14.00, 0.009114), (15.00, 0.00943), (16.00, 0.009747), (17.00, 0.01006), (18.00, 0.01038), (19.00, 0.0107), (20.00, 0.01101), (21.00, 0.01133), (22.00, 0.01165), (23.00, 0.01196), (24.00, 0.01228), (25.00, 0.01259), (26.00, 0.01291), (27.00, 0.01323), (28.00, 0.01354), (29.00, 0.01386), (30.00, 0.01418), (31.00, 0.01449), (32.00, 0.01481), (33.00, 0.01513), (34.00, 0.01544), (35.00, 0.01576), (36.00, 0.01608), (37.00, 0.01639), (38.00, 0.01671), (39.00, 0.01703), (40.00, 0.01734), (41.00, 0.01766), (42.00, 0.01797), (43.00, 0.01829), (44.00, 0.01861), (45.00, 0.01892), (46.00, 0.01924), (47.00, 0.01956), (48.00, 0.01987), (49.00, 0.02019), (50.00, 0.02051), (51.00, 0.02082), (52.00, 0.02114), (53.00, 0.02146), (54.00, 0.02177), (55.00, 0.02209), (56.00, 0.02241), (57.00, 0.02272), (58.00, 0.02304), (59.00, 0.02335), (60.00, 0.02367), (61.00, 0.02399), (62.00, 0.0243), (63.00, 0.02462), (64.00, 0.02494), (65.00, 0.02525), (66.00, 0.02557), (67.00, 0.02589), (68.00, 0.0262), (69.00, 0.02652), (70.00, 0.02684), (71.00, 0.02715), (72.00, 0.02747), (73.00, 0.02778), (74.00, 0.0281), (75.00, 0.02842), (76.00, 0.02873), (77.00, 0.02905), (78.00, 0.02937), (79.00, 0.02968), (80.00, 0.03)		
Minimum_demand_for_farmland	Per_capita_demand_for_farmland*Population		
Observed_fertility	"Desired_Number_of_Children_(DNC)"*Fraction_achieving_desired_family_size		1
Per_capita_demand_for_farmland	Per_capita_demand_for_grain/Farming_production.Yield		ha/year

Per_capita_demand_for_grain	0.146		ton/year/person
Population	Aged_65+"Aged_15-64"+"Aged_1-15"		
Rural_construction_demand	Rural_population*"Rural_land/_person"		
"Rural_land/_person"	0.0165		
Rural_population	Population*(1-Urbanization_rate)		
"Urban_and_industrial_land_/_person"	0.05676		
Urban_land_demand	Urban_population*"Urban_and_industrial_land_/_person"		
Urban_population	Population*Urbanization_rate		
Urbanization_rate	MIN(0.0001008*TIME*TIME+0.00732*TIME+0.1972, 0.80)		
Soil_conservation:			
Actual_Soil_Conservation_quantity	Rainfall_erosion_index*Soil_erosion_factor*"length-slope_index"*Vegetation_and_administration_element*support_practice_factor		t/(ha/yr)
"length-slope_index"	0.58		
Potential_Soil_conservation	Rainfall_erosion_index*Soil_erosion_factor*"length-slope_index"		t/(ha/yr
Precipitation_April	Climate_regulation.Precipitation*0.046664238		
Precipitation_August	Climate_regulation.Precipitation*0.176909357		
Precipitation_December	Climate_regulation.Precipitation*0.016539141		

Precipitation_February	Climate_regulation.Precipitation*0.022632564		
Precipitation_January	Climate_regulation.Precipitation*0.012001067		
Precipitation_July	Climate_regulation.Precipitation*0.247471656		
Precipitation_June	Climate_regulation.Precipitation*0.114109491		
Precipitation_March	Climate_regulation.Precipitation*0.033678072		
Precipitation_May	Climate_regulation.Precipitation*0.101434348		
Precipitation_November	Climate_regulation.Precipitation*0.036744414		
Precipitation_October	Climate_regulation.Precipitation*0.047308426		
Precipitation_September	Climate_regulation.Precipitation*0.091275505		
Rainfall_erosion_index	1.735 * (10^(1.5 * LOG10((Precipitation_January^2) / Climate_regulation.Precipitation) - 0.08188)) + 1.735 * (10^(1.5 * LOG10((Precipitation_February^2) / Climate_regulation.Precipitation) - 0.08188)) + 1.735 * (10^(1.5 * LOG10((Precipitation_March^2) / Climate_regulation.Precipitation) - 0.08188)) + 1.735 * (10^(1.5 * LOG10((Precipitation_April^2) / Climate_regulation.Precipitation) - 0.08188)) + 1.735 * (10^(1.5 * LOG10((Precipitation_May^2) / Climate_regulation.Precipitation) - 0.08188)) + 1.735 * (10^(1.5 * LOG10((Precipitation_June^2) / Climate_regulation.Precipitation) - 0.08188)) + 1.735 * (10^(1.5 * LOG10((Precipitation_July^2) / Climate_regulation.Precipitation) - 0.08188)) + 1.735 * (10^(1.5 * LOG10((Precipitation_August^2) / Climate_regulation.Precipitation) - 0.08188)) + 1.735 * (10^(1.5 * LOG10((Precipitation_September^2) / Climate_regulation.Precipitation) - 0.08188)) + 1.735 * (10^(1.5 * LOG10((Precipitation_October^2) / Climate_regulation.Precipitation) - 0.08188)) + 1.735 * (10^(1.5 * LOG10((Precipitation_November^2) / Climate_regulation.Precipitation) - 0.08188)) + 1.735 *		MJ/mm/(ha/h/a)

	(10^(1.5 * LOG10((Precipitation_December^2) / Climate_regulation.Precipitation) - 0.08188))		
Soil_Conservation_quantity	(Potential_Soil_conservation-Actual_Soil_Conservation_quantity)		t/(ha/yr)
Soil_erosion_factor	(0.2+0.3*EXP(-0.0256*45*(1-30/100)))* (1-(0.25*5/5+EXP(3.72-(2.95*5))))* (1-(0.7*(1- 45/100))/(1-45/100+EXP(-5.51+22.9*(1-45/100))))* (30/20+30)^0.3		
support_practice_factor	0.2105		
Vegetation_and_administration_element	(0.003 * "Land_use/_land_cover".Forestland+ 0.02 * "Land_use/_land_cover".Grassland + 0.3 * "Land_use/_land_cover".Cultivated_land+0.8*"Land_use/_land_cover".Barren_land) /15463288.53		
Wastewater_discharge:			
Wastewater_discharge	IF TIME <26 THEN (0.000000050683 * GDP.GDP + 0.013302 * Population.Population -109310* Population.Urbanization_rate -963100) ELSE(370000)		
Water_balance:			
Amount_of_penetration	Coefficient_of_permeability*"Land_use/_land_cover".Water_covered_land*10		
Average_water_depth	GRAPH(Climate_regulation.Precipitation) Points: (620.0, 1.000), (624.482758621, 1.069), (628.965517241, 1.138), (633.448275862, 1.207), (637.931034483, 1.276), (642.413793103, 1.345), (646.896551724, 1.414), (651.379310345, 1.483), (655.862068966, 1.552), (660.344827586, 1.621), (664.827586207, 1.690), (669.310344828, 1.759), (673.793103448, 1.828), (678.275862069, 1.897), (682.75862069, 1.966), (687.24137931, 2.034), (691.724137931, 2.103), (696.206896552, 2.172), (700.689655172, 2.241), (705.172413793, 2.310), (709.655172414, 2.379), (714.137931034, 2.448), (718.620689655, 2.517), (723.103448276, 2.586), (727.586206897, 2.655), (732.068965517, 2.724), (736.551724138, 2.793), (741.034482759, 2.862), (745.517241379, 2.931), (750.0, 3.000)		Meters
Coefficient_of_permeability	150		

ecologic_water	GRAPH(TIME) Points: (11.00, 34000000), (11.95, 29000000), (12.90, 138000000), (13.85, 168000000), (14.80, 237000000), (15.75, 262000000), (16.70, 3.2e+08), (17.65, 373000000), (18.60, 394000000), (19.55, 4.9e+08), (20.50, 5.4e+08), (21.45, 6.1e+08), (22.40, 6.7e+08), (23.35, 695000000), (24.30, 7.9e+08), (25.25, 1.01e+09), (26.20, 1.15e+09), (27.15, 1.5e+09), (28.10, 1.66e+09), (29.05, 1908000000), (30.00, 2.13e+09)		
Evaporation_flow	Water_yield.Reference_ET0*"Land_use/_land_cover".Water_covered_land*10		
Industry_water	GRAPH(GDP.Secondary_GDP) Points: (446674000000, 4.17e+09), (503763000000, 3.86e+09), (572001000000, 3.35e+09), (732761000000, 2.26e+09), (884113000000, 1.71e+09), (1056849000000, 1.71e+09), (1252941000000, 2.15e+09), (1491150000000, 2.22e+09), (1591967000000, 2.37e+09), (1773308000000, 2.54e+09), (1992611000000, 2.7e+09), (2127589000000, 2.83e+09), (2261589000000, 2.89e+09), (2358802000000, 2.94e+09), (2481488000000, 3e+09), (2556504000000, 3.07e+09), (2692559000000, 3.13e+09), (2752367000000, 3.16e+09), (2817178000000, 3.18e+09), (2845666000000, 3.2e+09)		
"Inter-basin_water_transfer"	GRAPH(TIME) Points: (1.00, 0), (1.96666666667, 0), (2.93333333333, 0), (3.90, 0), (4.86666666667, 0), (5.83333333333, 0), (6.80, 0), (7.76666666667, 0), (8.73333333333, 0), (9.70, 0), (10.6666666667, 4.93e+08), (11.6333333333, 5.04e+08), (12.60, 5.12e+08), (13.5666666667, 5.16e+08), (14.5333333333, 5.31e+08), (15.50, 5.39e+08), (16.4666666667, 5.5e+08), (17.4333333333, 5.58e+08), (18.40, 5.77e+08), (19.3666666667, 5.81e+08), (20.3333333333, 5.92e+08), (21.30, 5.96e+08), (22.2666666667, 6.03e+08), (23.2333333333, 6.07e+08), (24.20, 6.11e+08), (25.1666666667, 6.23e+08), (26.1333333333, 6.34e+08), (27.10, 6.42e+08), (28.0666666667, 6.49e+08), (29.0333333333, 6.65e+08), (30.00, 6.72e+08)		(cubic meter))
Life_water_consumption	"water_consumption/people"*Population.Population		
"Surface_water_consumption(SWC)"	Amount_of_penetration+Evaporation_flow+("SWC-life_water"+"SWC-industry_water"+"SWC-irrigation"+"SWC-ecological_water")		cubic meter
"SWC_rate-"	GRAPH(TIME) Points: (1.00, 0.0500), (2.00, 0.07759), (3.00, 0.1052), (4.00, 0.1328), (5.00, 0.1603), (6.00, 0.1879), (7.00, 0.2155), (8.00, 0.2431), (9.00, 0.2707),		

ecologic water"	(10.00, 0.2983), (11.00, 0.3259), (12.00, 0.3534), (13.00, 0.3810), (14.00, 0.4086), (15.00, 0.4362), (16.00, 0.4638), (17.00, 0.4914), (18.00, 0.5190), (19.00, 0.5466), (20.00, 0.5741), (21.00, 0.6017), (22.00, 0.6293), (23.00, 0.6569), (24.00, 0.6845), (25.00, 0.7121), (26.00, 0.7397), (27.00, 0.7672), (28.00, 0.7948), (29.00, 0.8224), (30.00, 0.8500)		
"SWC_rate- _industry_ water"	GRAPH(TIME) Points: (1.00, 0.5500), (2.00, 0.5545), (3.00, 0.5590), (4.00, 0.5634), (5.00, 0.5679), (6.00, 0.5724), (7.00, 0.5769), (8.00, 0.5814), (9.00, 0.5859), (10.00, 0.5903), (11.00, 0.5948), (12.00, 0.5993), (13.00, 0.6038), (14.00, 0.6083), (15.00, 0.6128), (16.00, 0.6172), (17.00, 0.6217), (18.00, 0.6262), (19.00, 0.6307), (20.00, 0.6352), (21.00, 0.6397), (22.00, 0.6441), (23.00, 0.6486), (24.00, 0.6531), (25.00, 0.6576), (26.00, 0.6621), (27.00, 0.6666), (28.00, 0.6710), (29.00, 0.6755), (30.00, 0.6800)		
"SWC_rate- _life_water"	GRAPH(TIME) Points: (1.00, 0.4500), (2.00, 0.4541), (3.00, 0.4583), (4.00, 0.4624), (5.00, 0.4666), (6.00, 0.4707), (7.00, 0.4748), (8.00, 0.4790), (9.00, 0.4831), (10.00, 0.4872), (11.00, 0.4914), (12.00, 0.4955), (13.00, 0.4997), (14.00, 0.5038), (15.00, 0.5079), (16.00, 0.5121), (17.00, 0.5162), (18.00, 0.5203), (19.00, 0.5245), (20.00, 0.5286), (21.00, 0.5328), (22.00, 0.5369), (23.00, 0.5410), (24.00, 0.5452), (25.00, 0.5493), (26.00, 0.5534), (27.00, 0.5576), (28.00, 0.5617), (29.00, 0.5659), (30.00, 0.5700)		
"SWC_rate -irrigation"	GRAPH(TIME) Points: (1.00, 0.65), (2.00, 0.6483), (3.00, 0.6466), (4.00, 0.6448), (5.00, 0.6431), (6.00, 0.6414), (7.00, 0.6397), (8.00, 0.6379), (9.00, 0.6362), (10.00, 0.6345), (11.00, 0.6328), (12.00, 0.631), (13.00, 0.6293), (14.00, 0.6276), (15.00, 0.6259), (16.00, 0.6241), (17.00, 0.6224), (18.00, 0.6207), (19.00, 0.619), (20.00, 0.6172), (21.00, 0.6155), (22.00, 0.6138), (23.00, 0.6121), (24.00, 0.6103), (25.00, 0.6086), (26.00, 0.6069), (27.00, 0.6052), (28.00, 0.6034), (29.00, 0.6017), (30.00, 0.6)		
"SWC-ecological _water"	ecologic_water*(MIN("SWC_rate-_ecologic_water", 1))		
"SWC-industry_water"	Industry_water*(MIN("SWC_rate-_industry_water", 0.8))		
"SWC-irrigation"	Farming_production.Irrigation*(MIN("SWC_rate-irrigation", 0.8))		
"SWC-life_water"	Life_water_consumption*(MIN("SWC_rate-_life_water", 1))		
"water_consumption/people"	GRAPH(TIME) Points: (11.00, 23.00), (11.95, 24.08), (12.90, 25.11), (13.85, 26.08), (14.80, 27.01), (15.75, 27.90), (16.70, 28.74), (17.65, 29.54), (18.60, 30.30),		

	(19.55, 31.03), (20.50, 31.71), (21.45, 32.37), (22.40, 32.99), (23.35, 33.59), (24.30, 34.15), (25.25, 34.69), (26.20, 35.20), (27.15, 35.68), (28.10, 36.14), (29.05, 36.58), (30.00, 37.00)		
Water_flow	((water_inflow-"Surface_water_consumption(SWC)")/(MAX(Average_water_depth, 0.1)*10000))		
water_inflow	"Water_yield_(cubic_meter)"+"Inter-basin_water_transfer"+Wastewater_discharge.Wastewater_discharge*0.6		cubic meter
"Water_yield_(cubic_meter)"	Water_yield.Water_Yield*11463289*10		cubic meter
Water_yield:			
"Barren_AET/P"	1+(Barren_PET/Climate_regulation.Precipitation)-(1+(Barren_PET/Climate_regulation.Precipitation)^"w-barren")^(1/"w-barren")		
Barren_AWC	0.5*("PAWC-The_amount_of_water_available_to_the_plants")		
Barren_PET	0.2*Reference_ET0		
Barren_water_yield	(1-"Barren_AET/P")*Climate_regulation.Precipitation		
Clay_rate	20*(1+0.5*(Soil_conservation.Soil_Conservation_quantity-INIT(Soil_conservation.Soil_Conservation_quantity))/INIT(Soil_conservation.Soil_Conservation_quantity))		
Construction_AWC	0.1*("PAWC-The_amount_of_water_available_to_the_plants")		
Construction_land_water_yield	(1-Urban_PET/Climate_regulation.Precipitation)*Climate_regulation.Precipitation		
"cultivated_AET/P"	1+(cultivated_PET/Climate_regulation.Precipitation)-(1+(cultivated_PET/Climate_regulation.Precipitation)^"w-cultivated")^(1/"w-cultivated")		
Cultivated_AWC	3.5*("PAWC-The_amount_of_water_available_to_the_plants")		

cultivated_PET	0.68*Reference_ET0		
Cultivated_water_yield	(1-"cultivated_AET/P")*Climate_regulation.Precipitation		
"Forest_AET/P"	1+(Forest_PET/Climate_regulation.Precipitation)-(1+(Forest_PET/Climate_regulation.Precipitation)^"w-forest")^(1/"w-forest")		
Forest_AWC	5.2*("PAWC-The_amount_of_water_available_to_the_plants")		
Forest_PET	1*Reference_ET0		
Forest_water_yield	(1-"Forest_AET/P")*Climate_regulation.Precipitation		
"Grassland_AET/P"	1+(Grassland_PET/Climate_regulation.Precipitation)-(1+(Grassland_PET/Climate_regulation.Precipitation)^"w-grassland")^(1/"w-grassland")		
Grassland_AWC	2.5*("PAWC-The_amount_of_water_available_to_the_plants")		
Grassland_PET	Reference_ET0*0.85		
Grassland_water_yield	(1-"Grassland_AET/P")*Climate_regulation.Precipitation		
Organic_material_rate	5*(1+0.6*(Soil_conservation.Soil_Conservation_quantity-INIT(Soil_conservation.Soil_Conservation_quantity))/INIT(Soil_conservation.Soil_Conservation_quantity))		
"PAWC-The_amount_of_water_available_to_the_plants"	54.509 - (0.132 * Sand_rate) - (0.003 * Sand_rate^2) - (0.055 * Silt_rate) - (0.006 * Silt_rate^2) + (0.738 * Clay_rate) - (0.007 * Clay_rate^2) - (2.688 * Organic_material_rate) + 0.501 *(Organic_material_rate)^2		
Reference_ET0	0.0023*1361*(Climate_regulation.Temperature+15.8)*SQRT(15-0.0123*Climate_regulation.Precipitation)^0.76*6		
Sand_rate	100-Organic_material_rate-Clay_rate-Silt_rate		
Silt_rate	30		
"urban_AET/P"	1+(Urban_PET/Climate_regulation.Precipitation)-(1+(Urban_PET/Climate_regulation.Precipitation)^"w-construction")^(1/"w-construction")		
Urban_PET	MIN(0.3*Reference_ET0, Climate_regulation.Precipitation)		

"w-barren"	0.2*20*(Barren_AWC/Climate_regulation.Precipitation)+7		
"w-construction"	0.2*20*(Construction_AWC/Climate_regulation.Precipitation)+7		
"w-cultivated"	0.2*20*(Cultivated_AWC/Climate_regulation.Precipitation)+7		
"w-forest"	0.2*20*(Forest_AWC/Climate_regulation.Precipitation)+7		
"w-grassland"	0.2*20*(Grassland_AWC/Climate_regulation.Precipitation)+7		
"w-water"	0.2*20*(Water_AWC/Climate_regulation.Precipitation)+7		
Water_AWC	0.1*("PAWC-The_amount_of_water_available_to_the_plants")		
Water_covered_land_water_yield	(1-"Water_land_AET/P")*Climate_regulation.Precipitation		
"Water_land_AET/P"	1+(water_land_PET/Climate_regulation.Precipitation)-(1+(water_land_PET/Climate_regulation.Precipitation)^"w-water")^(1/"w-water")		
water_land_PET	MIN(1*Reference_ET0, Climate_regulation.Precipitation)		
Water_Yield	(Cultivated_water_yield*"Land_use/_land_cover".Cultivated_land+Construction_land_water_yield*"Land_use/_land_cover".Construction_land+Forest_water_yield*"Land_use/_land_cover".Forestland+Water_covered_land_water_yield*"Land_use/_land_cover".Water_covered_land+Barren_water_yield*"Land_use/_land_cover".Barren_land+Grassland_water_yield*"Land_use/_land_cover".Grassland)/15463289		

6.3.12 Results of the statistical validation tests.

Table 6.3-4 Results of the statistical validation tests.

Model building: 1991-2005

Model validation: 2005-2020

Variable	Coefficient of determination (R_2)	Percent Bias (PBIAS)	RMSE-observations standard deviation ratio (RSR)	Discrepancy coefficient (U_0)

Population	0.95	0.14	0.23	0.00
Barren land	0.97	8.11	0.52	0.06
Construction land	0.99	-1.68	0.29	0.01
Cultivated land	0.98	0.27	0.26	0.00
Forest land	0.93	-2.22	0.40	0.01
Grassland	0.83	4.40	0.55	0.03
Water covered land	0.78	3.49	0.64	0.02
Farming production	0.91	1.85	0.46	0.01
Carbon emission	0.97	-9.02	0.83	0.05
GDP	0.99	7.19	0.22	0.04

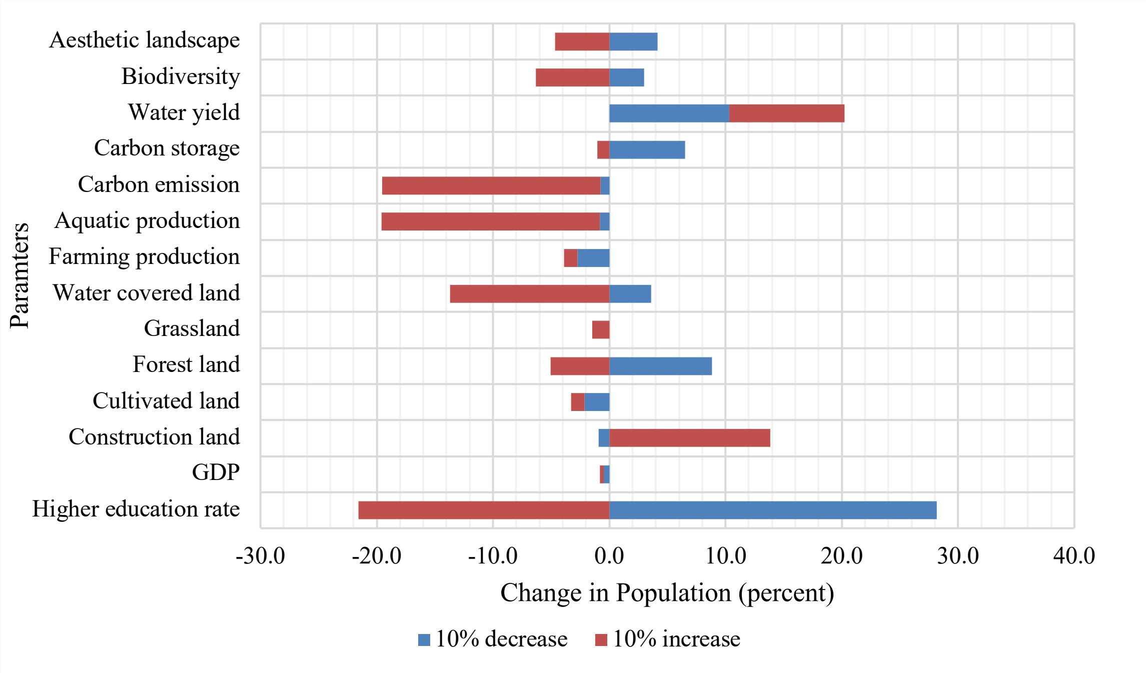
Note: Coefficient of determination (R^2) value close to 1.0 indicates the model simulates well;

PBIAS value < ± 10% indicates good model fit;

RSR value ≤ 0.50 indicates good model fit.

The U_0 values range from 0 to 1, where 0 indicates 'perfect prediction' and 1 indicates 'worse prediction' of the model behaviour.

6.3.13 One parameter at time sensitivity analyses



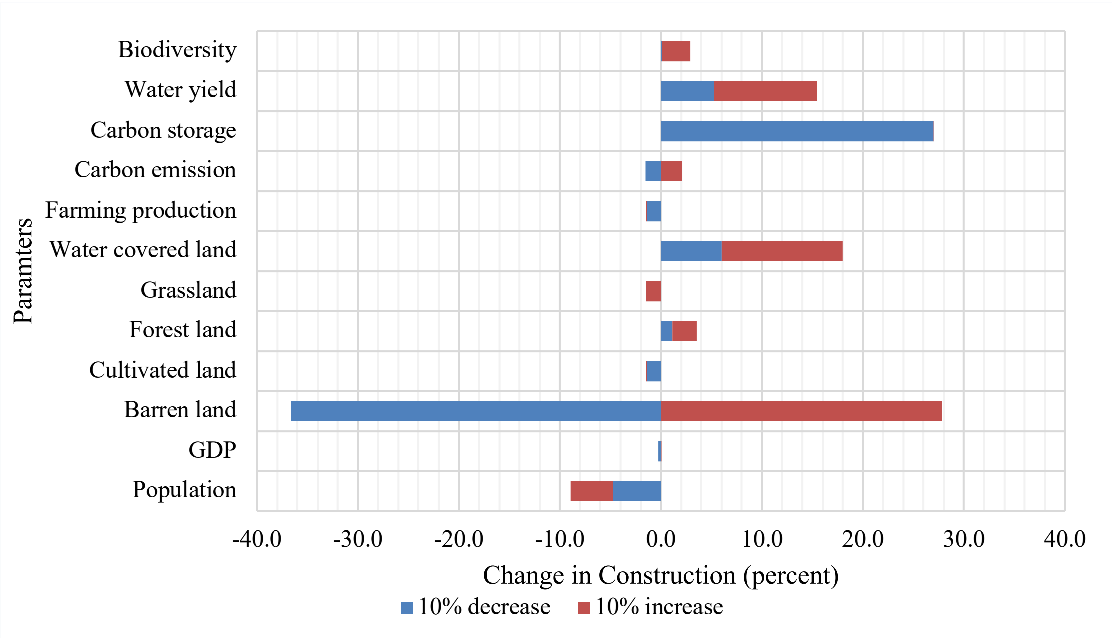
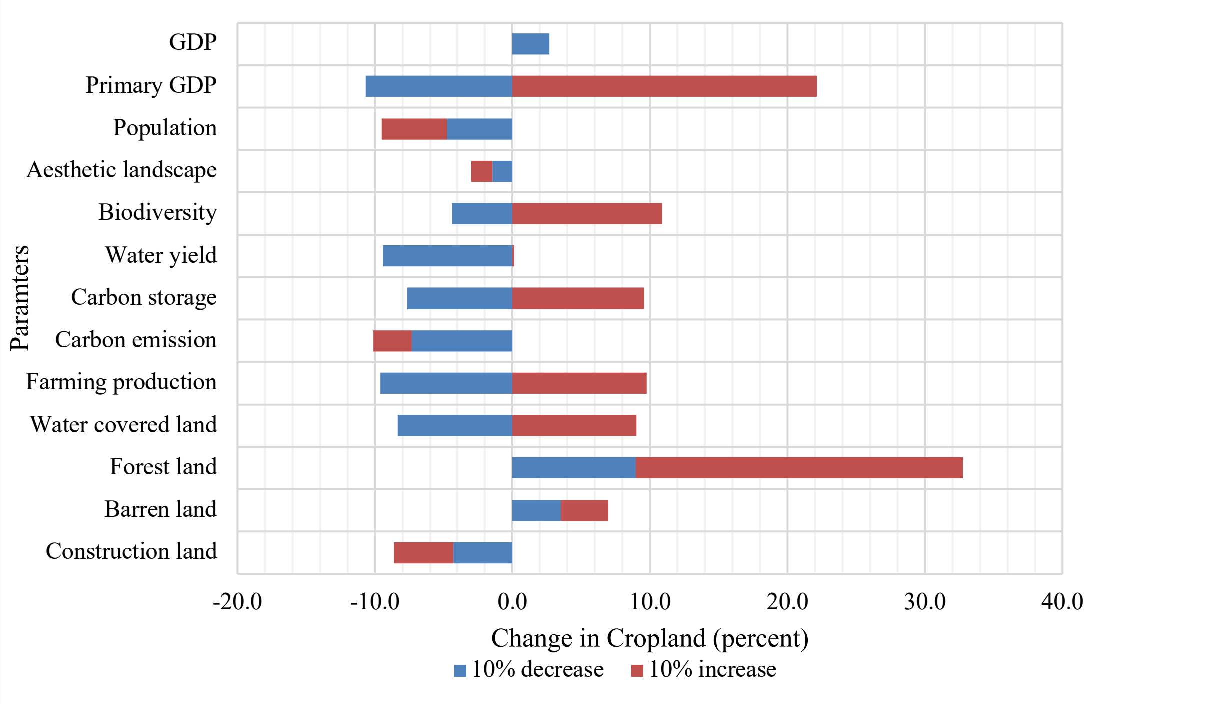


Figure 6.3-11 Outputs of the one parameter at time sensitivity analyses(Continue).



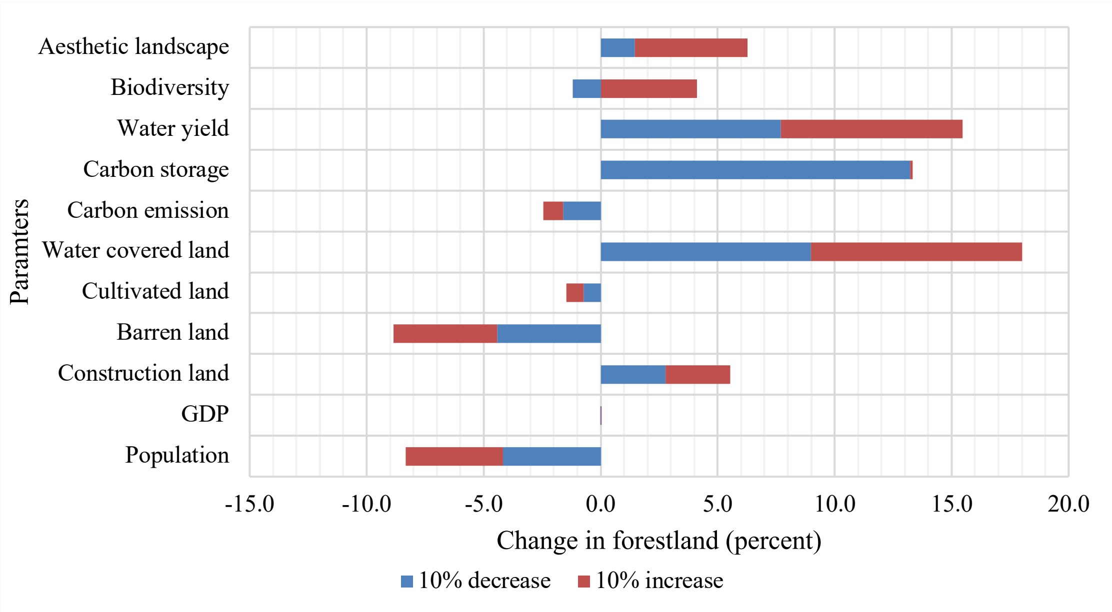
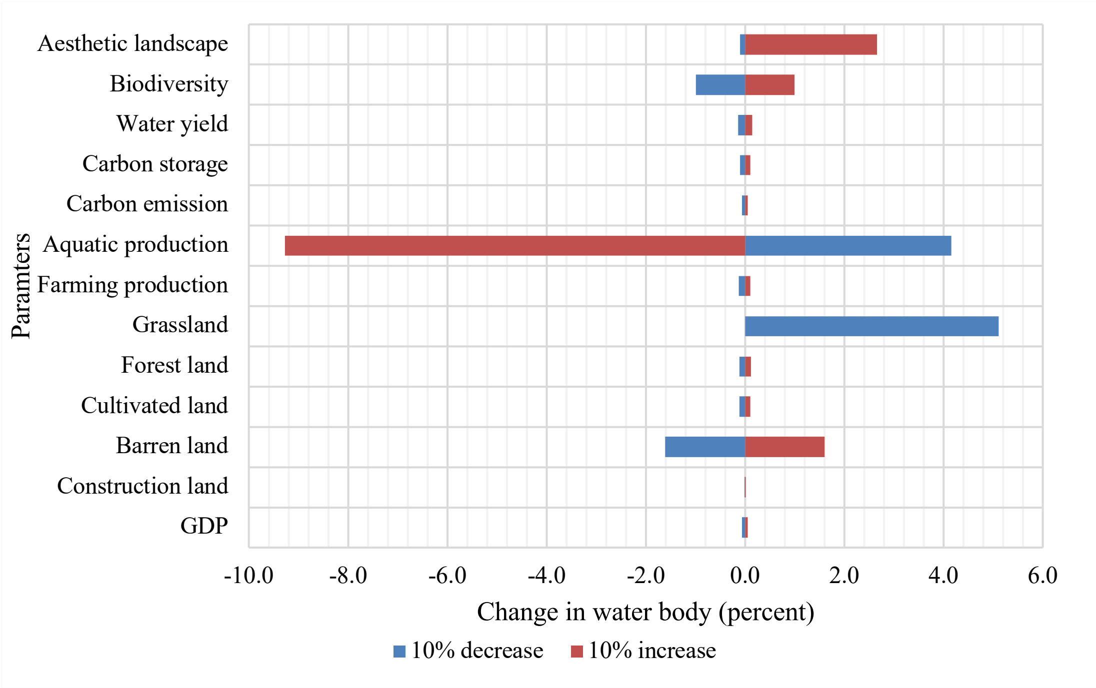


Figure 6.3-11 Outputs of the one parameter at time sensitivity analyses(Continue).



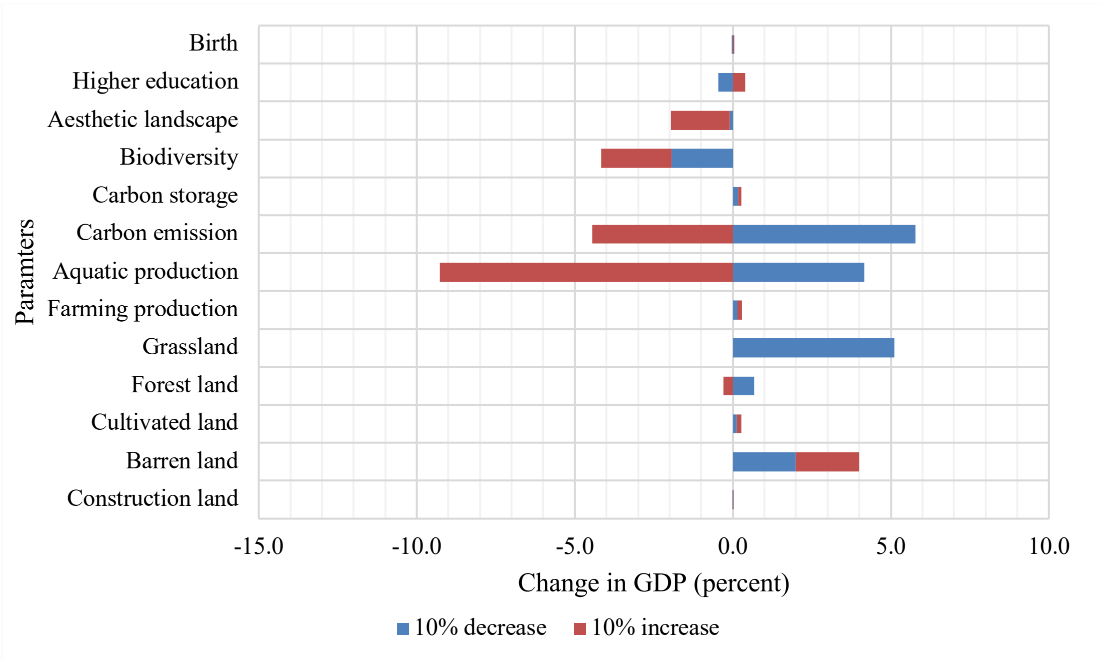
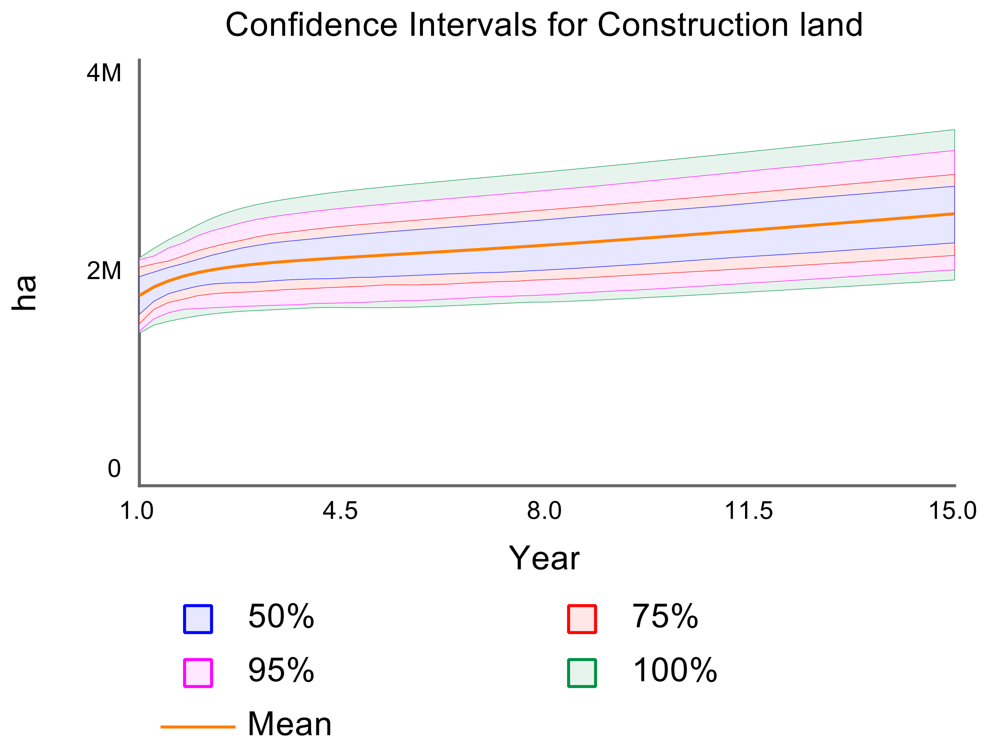
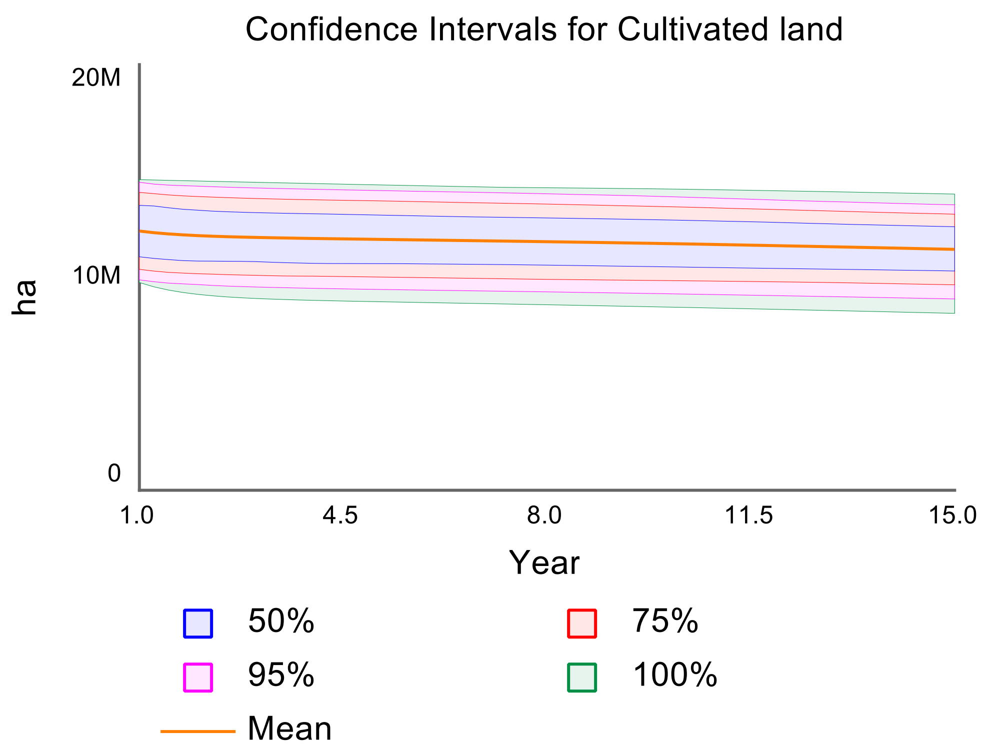
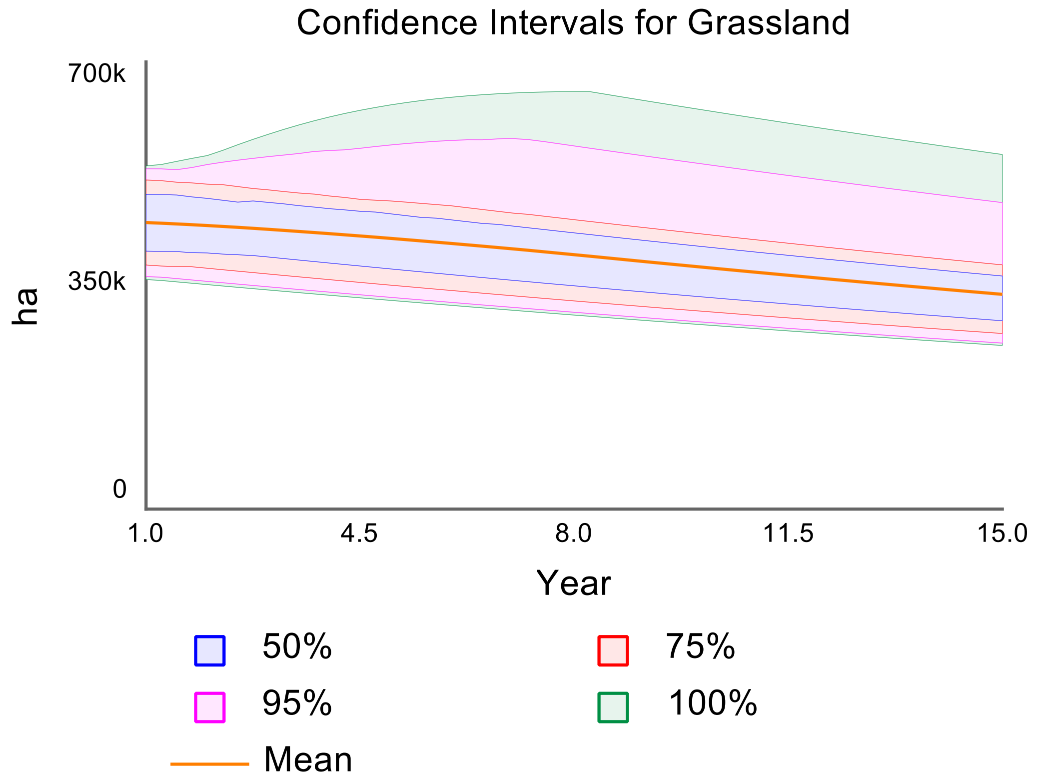


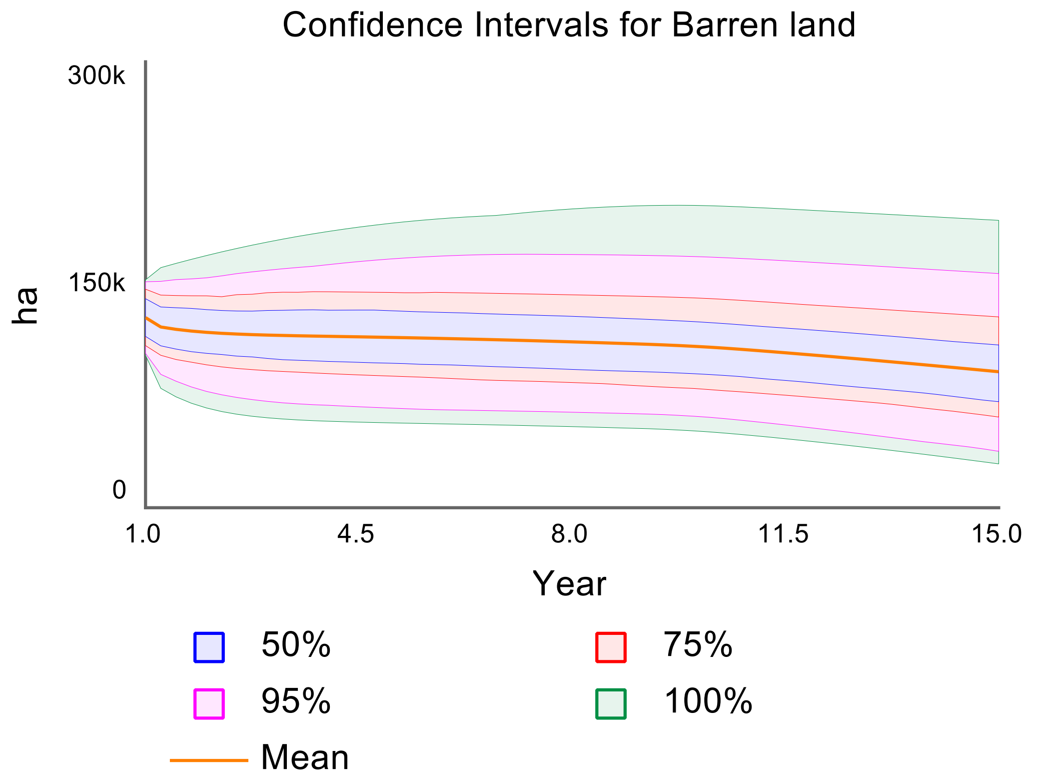
Figure 6.3-11 Outputs of the one parameter at time sensitivity analyses.

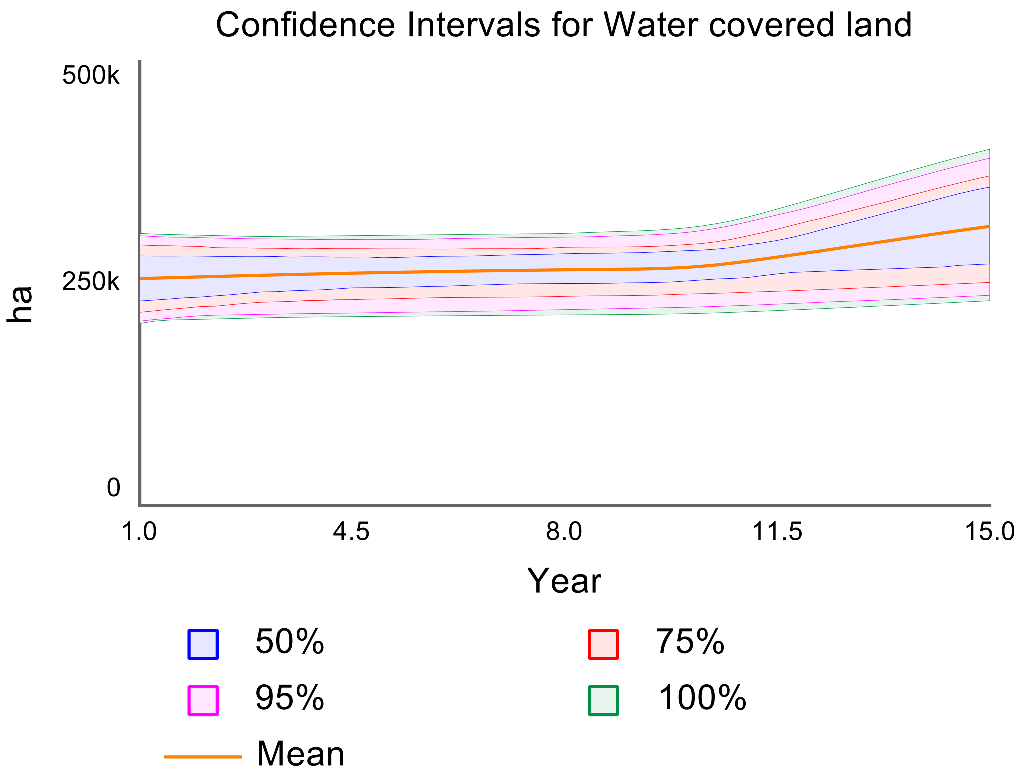
6.3.14 Monte Carlo Sensitivity analysis

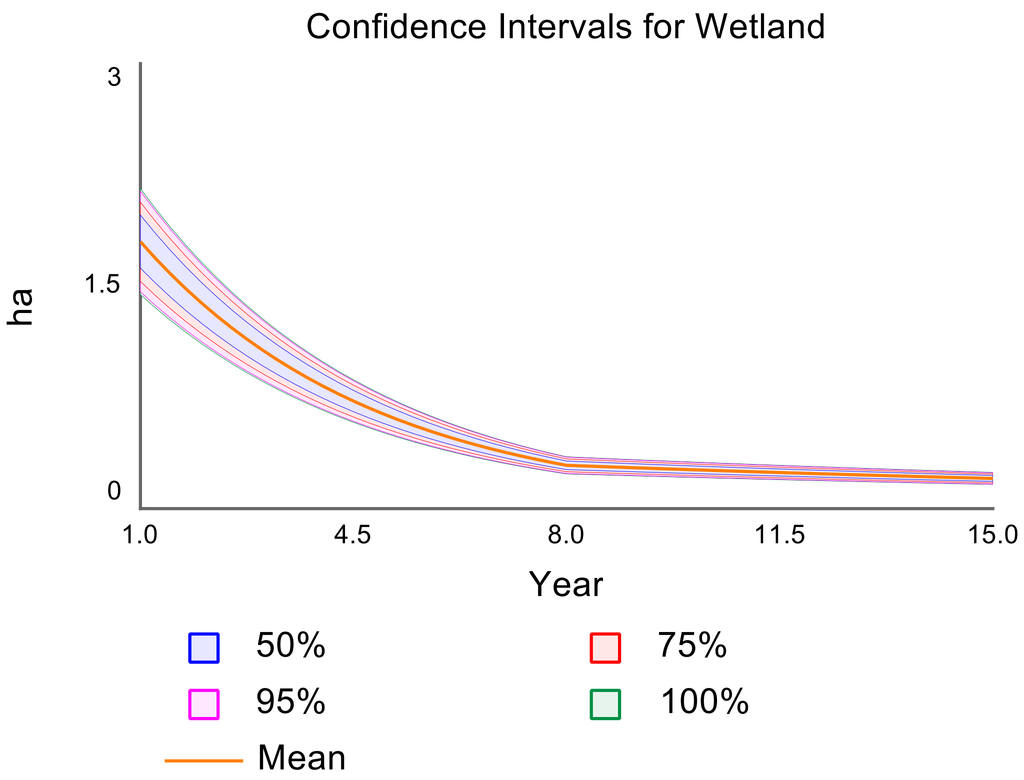


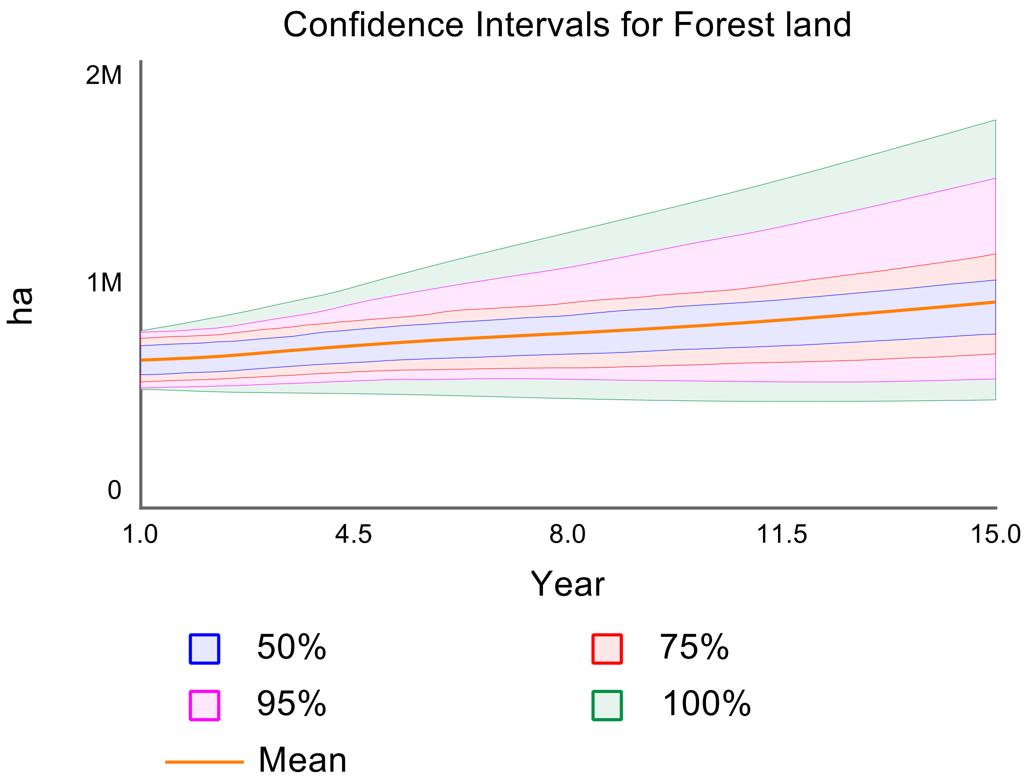


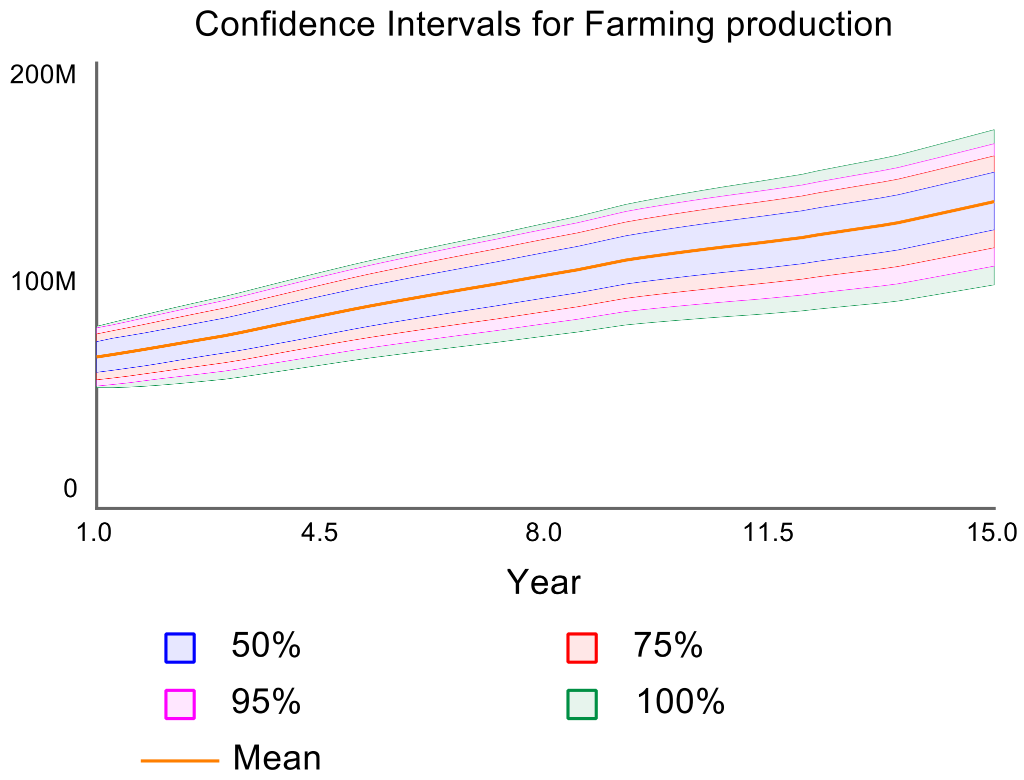

Confidence Intervals for Grassland
700k
350k
0
ha
1.0
4.5
8.0
11.5
15.0
Year
50%
75%
95%
100%
Mean

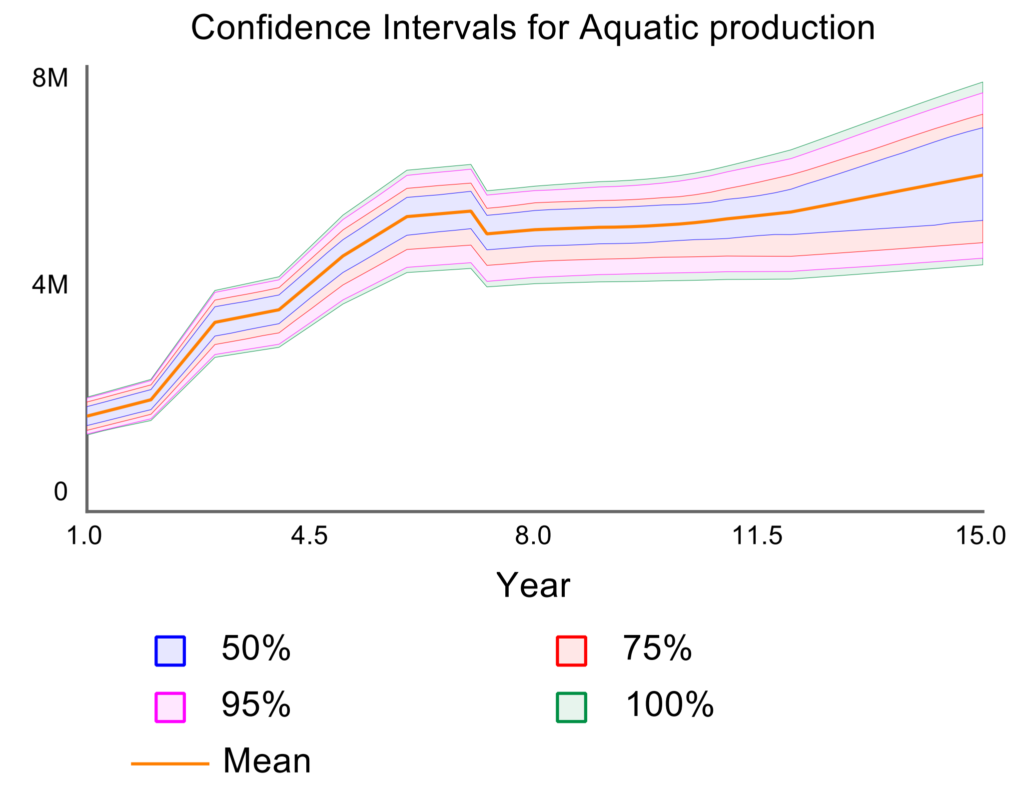

Confidence Intervals for Barren land
300k
150k
0
ha
1.0
4.5
8.0
11.5
15.0
Year
50%
75%
95%
100%
Mean

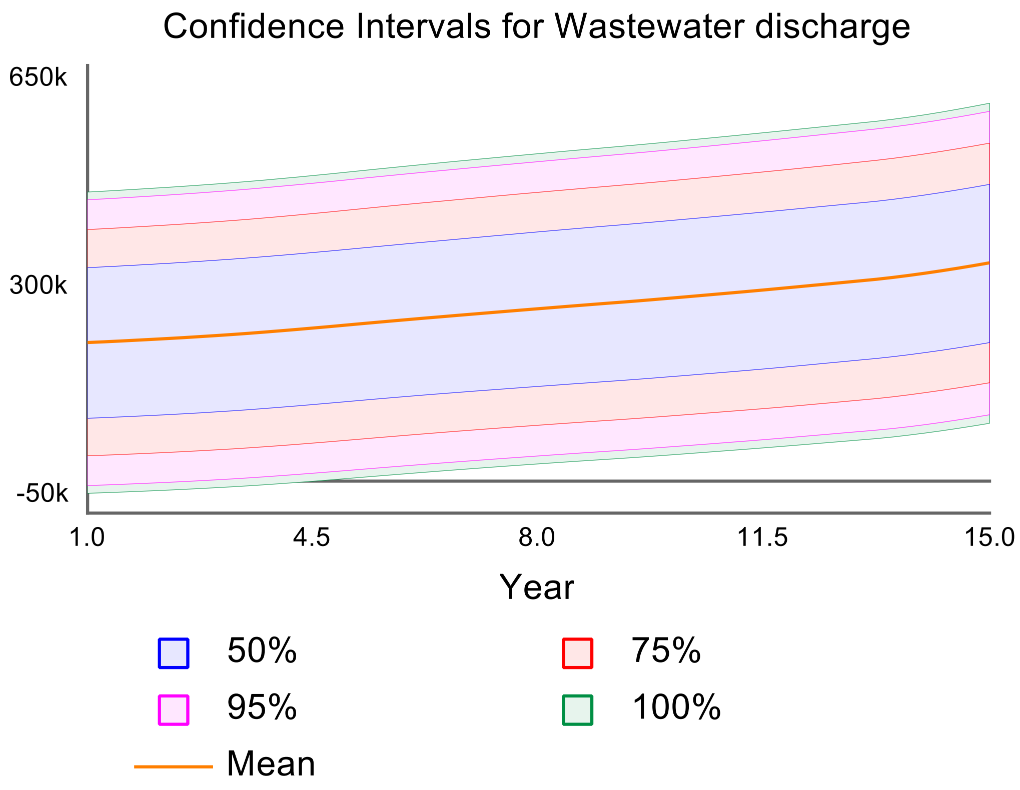

Confidence Intervals for Water covered land
500k
250k
0
ha
1.0
4.5
8.0
11.5
15.0
Year
50%
75%
95%
100%
Mean

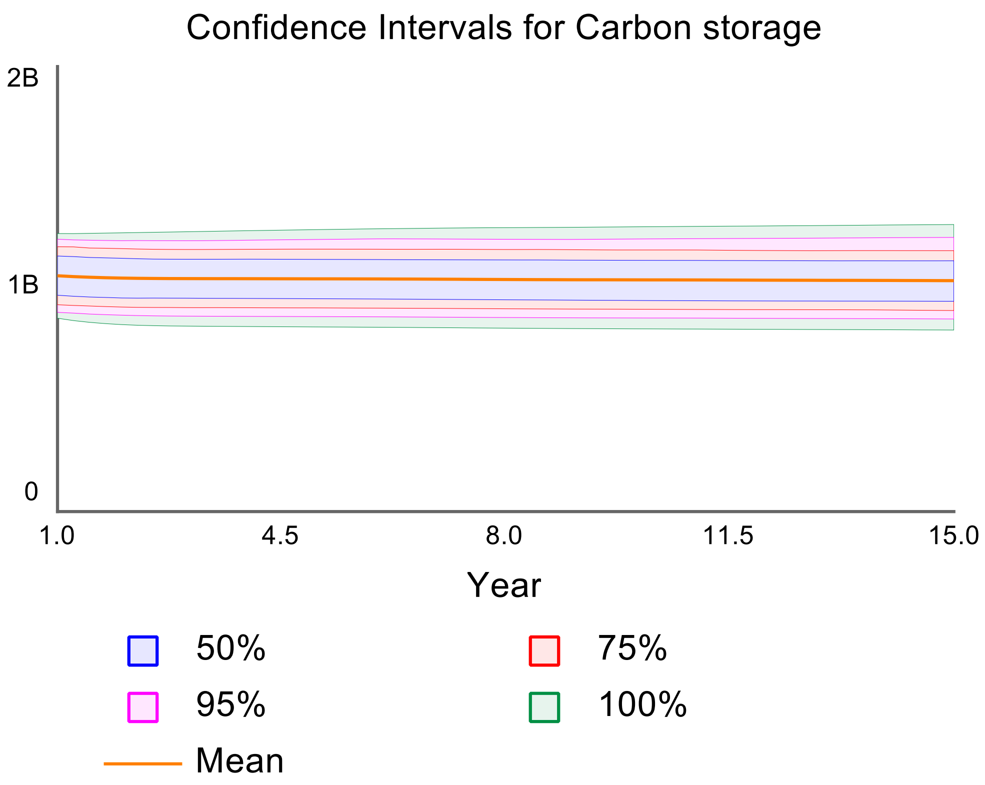

Confidence Intervals for Wetland
3
1.5
0
ha
1.0
4.5
8.0
11.5
15.0
Year
50%
75%
95%
100%
Mean

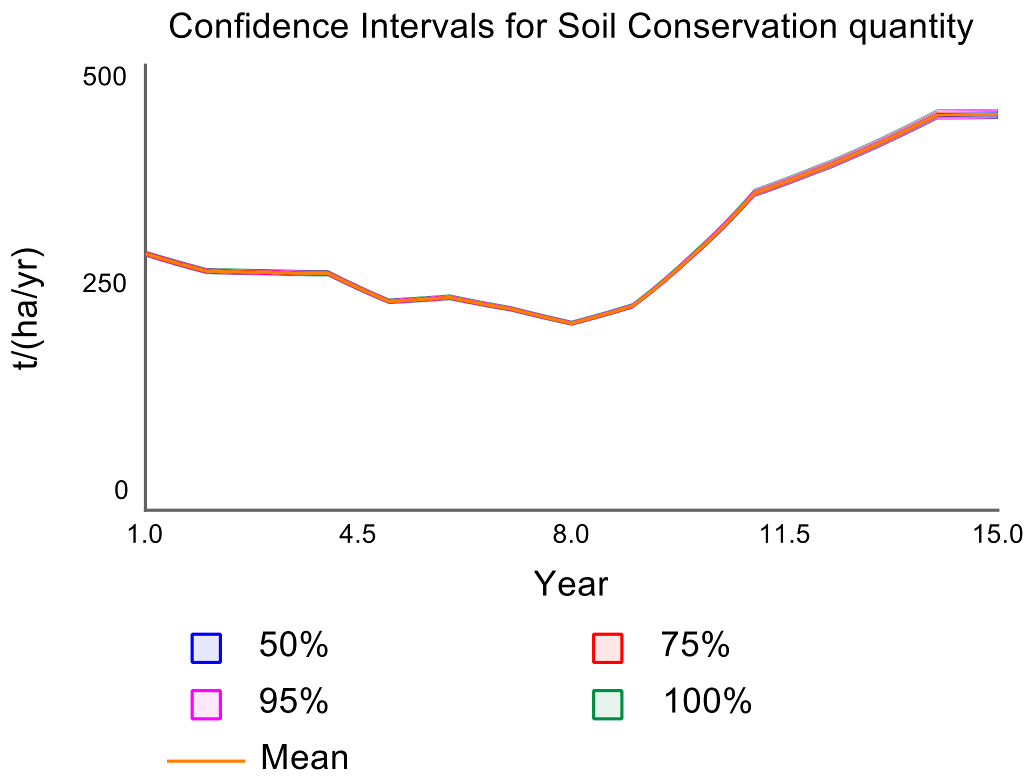

Confidence Intervals for Forest land
2M
1M
0
ha
1.0
4.5
8.0
11.5
15.0
Year
50%
75%
95%
100%
Mean

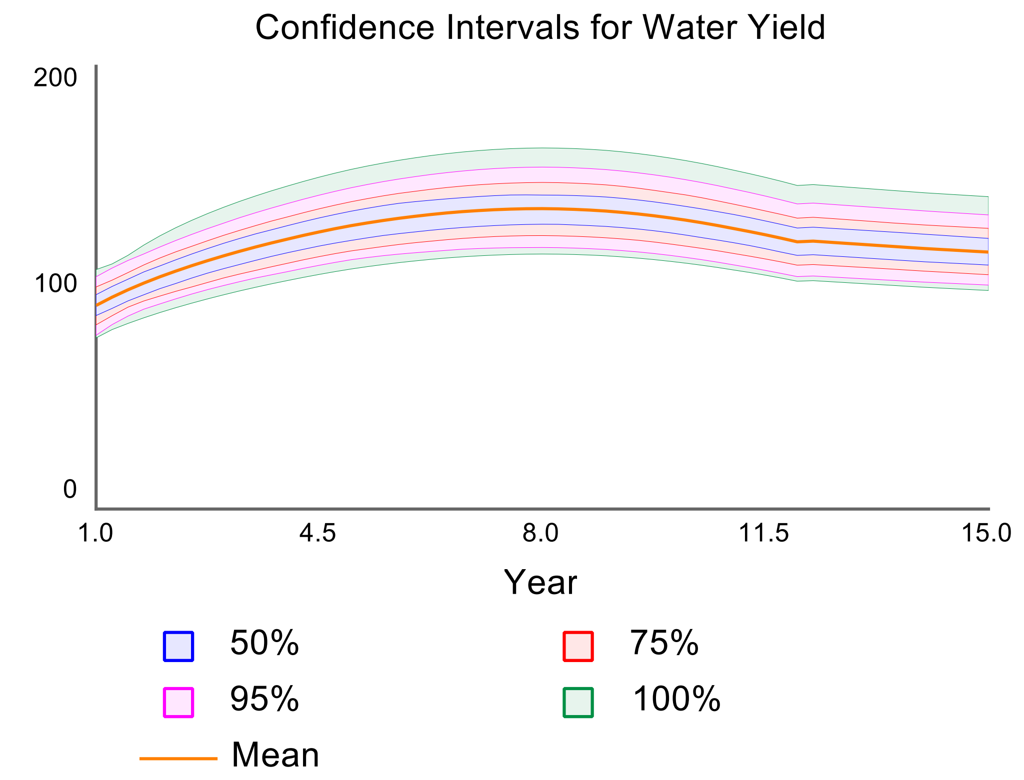

Confidence Intervals for Farming production
200M
100M
0
1.0
4.5
8.0
11.5
15.0
Year
50%
75%
95%
100%
Mean


Confidence Intervals for Aquatic production
8M
4M
0
1.0
4.5
8.0
11.5
15.0
Year
50%
75%
95%
100%
Mean

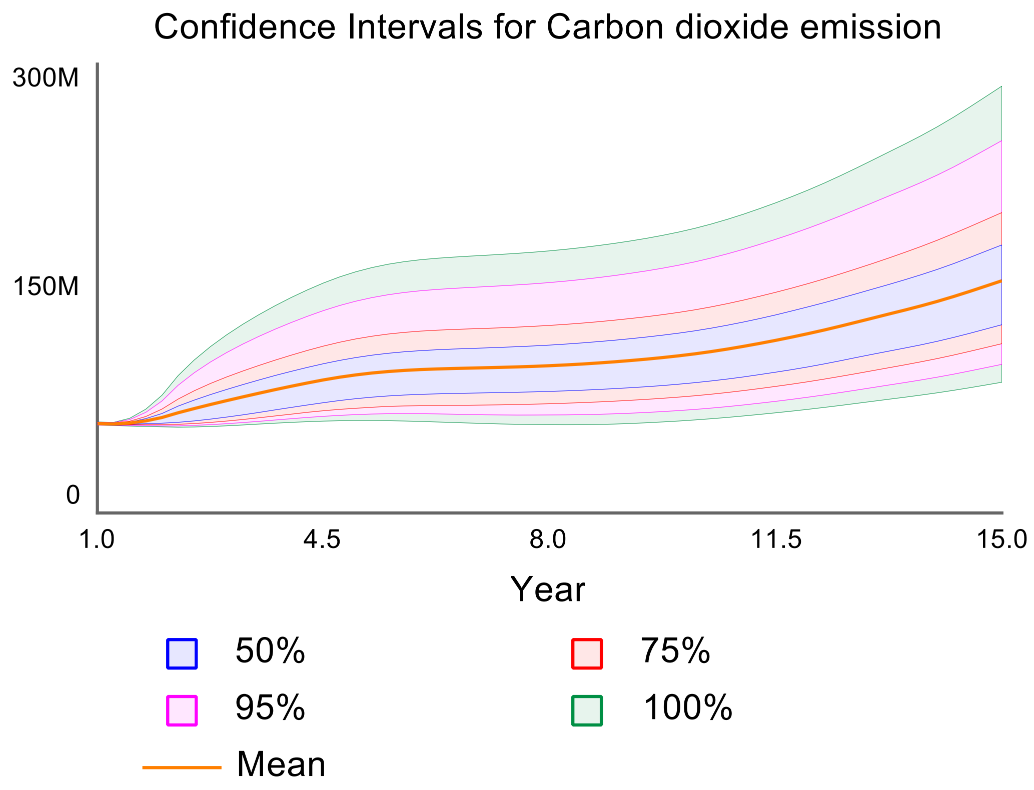

Confidence Intervals for Wastewater discharge
650k
300k
-50k
1.0
4.5
8.0
11.5
15.0
Year
50%
75%
95%
100%
Mean


Confidence Intervals for Carbon storage
2B
1B
0
1.0
4.5
8.0
11.5
15.0
Year
50%
75%
95%
100%
Mean

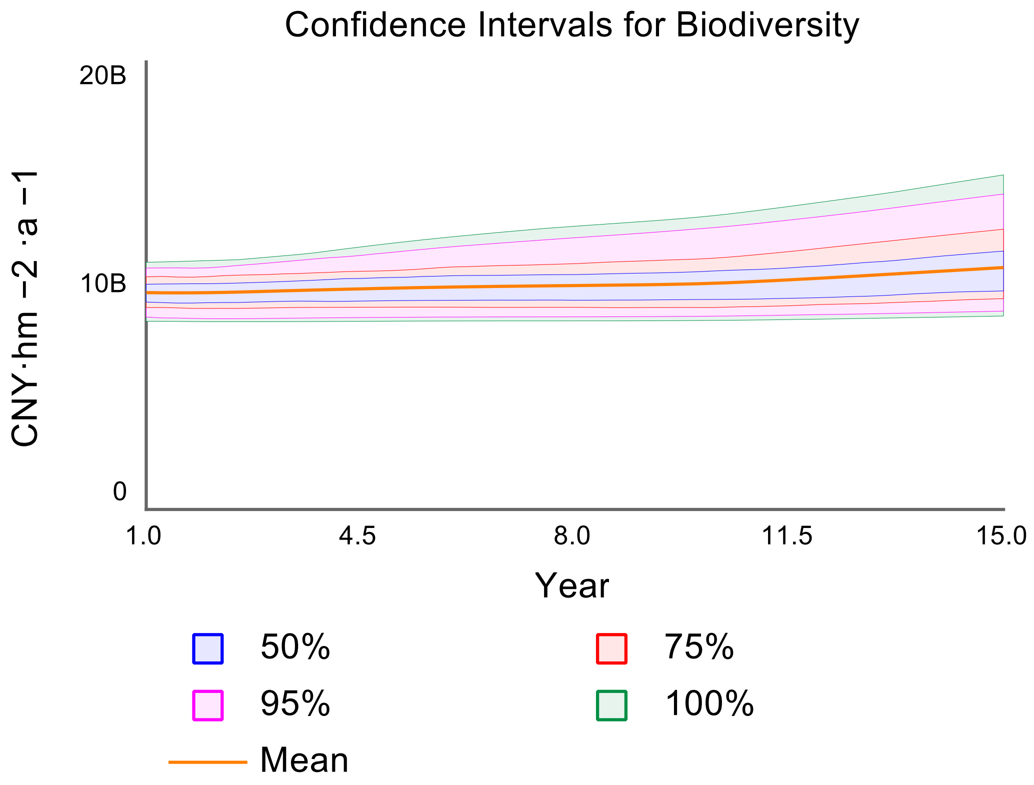

Confidence Intervals for Soil Conservation quantity
500
250
0
t/(ha/yr)
1.0
4.5
8.0
11.5
15.0
Year
50%
75%
95%
100%
Mean

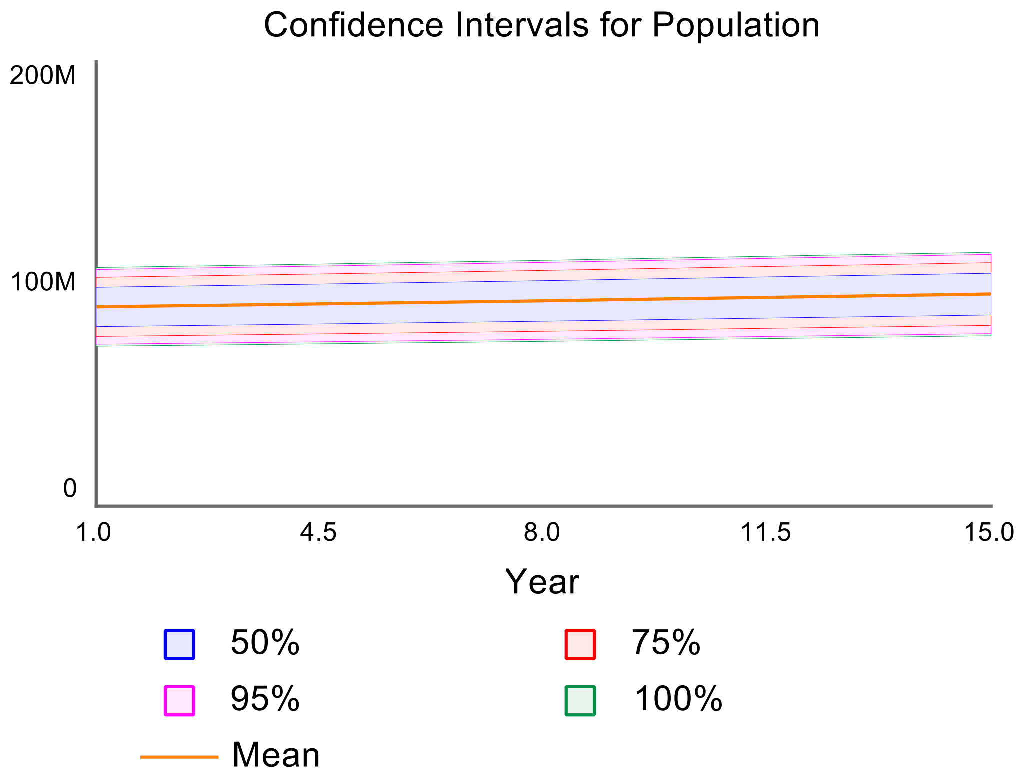


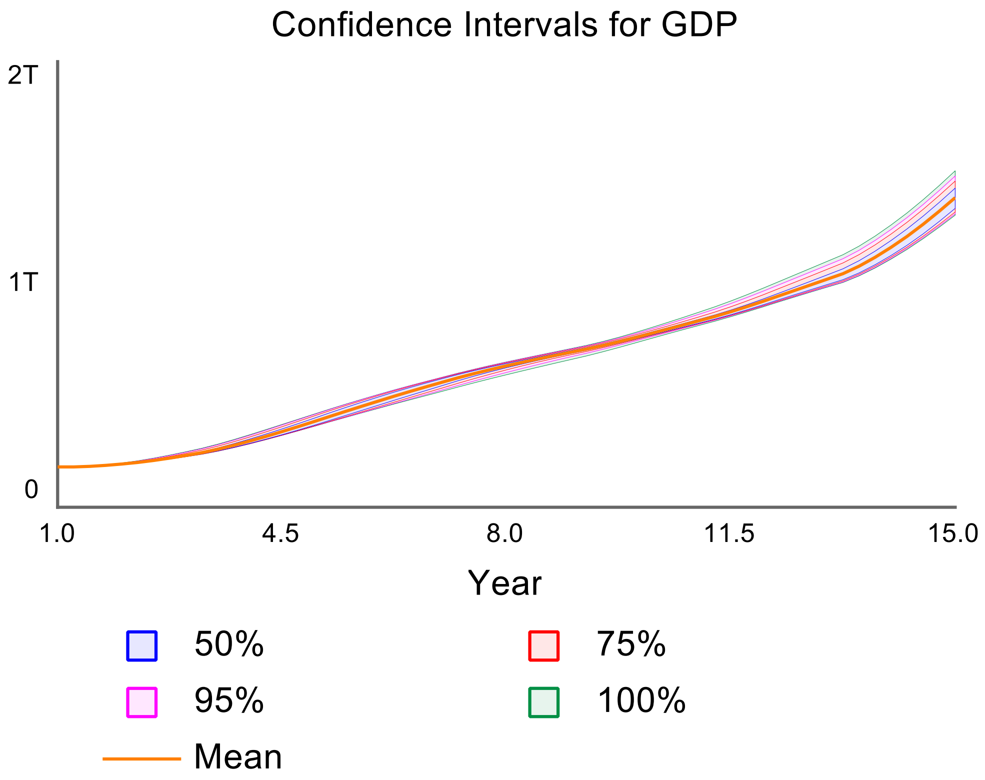
Confidence Intervals for Water Yield
200
100
0
1.0
4.5
8.0
11.5
15.0
Year
50%
75%
95%
100%
Mean



Confidence Intervals for Carbon dioxide emission
300M
150M
0
1.0
4.5
8.0
11.5
15.0
Year
50%
75%
95%
100%
Mean


Confidence Intervals for Biodiversity
20B
10B
0
CNY·hm −2 ·a −1
1.0
4.5
8.0
11.5
15.0
Year
50%
75%
95%
100%
Mean


Confidence Intervals for Population
200M
100M
0
1.0
4.5
8.0
11.5
15.0
Year
50%
75%
95%
100%
Mean



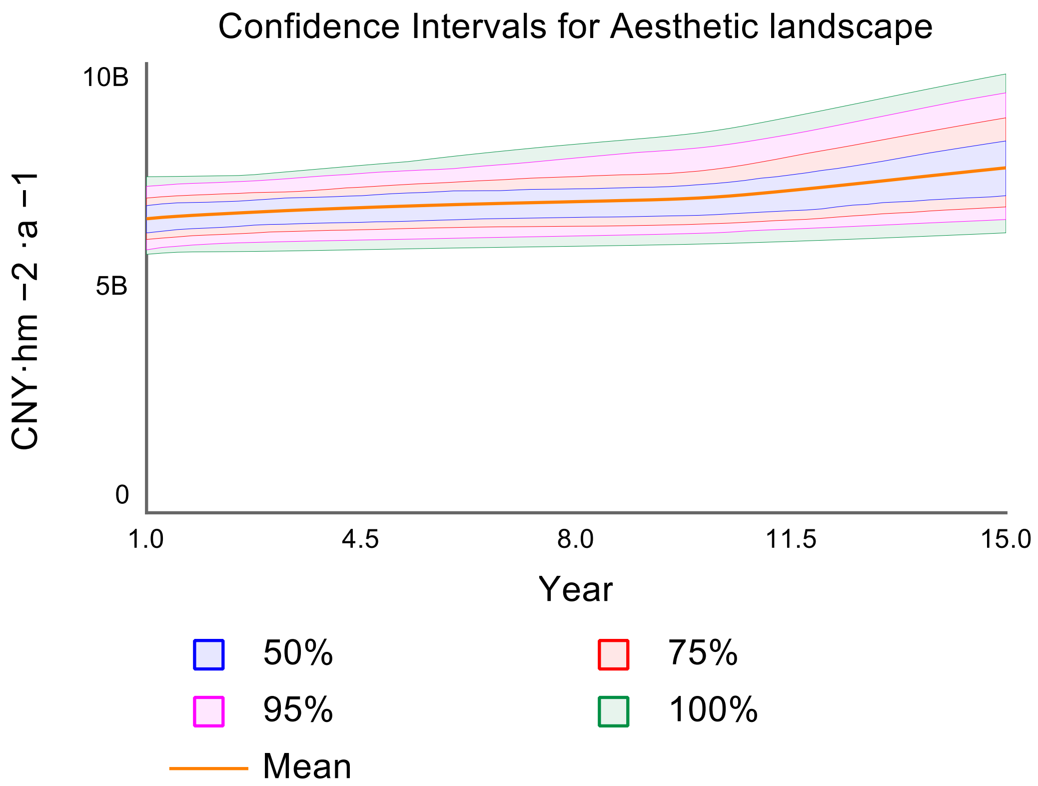


Figure 6.3-12 Outcomes of the Monte Carlo Sensitivity analysis. Parameter used for this analysis are -Population, construction land, forestland, cultivated land, grassland, barren land, water covered land, wetland, urban and industrial land/ person, rural land/ person. The wider the confidence bound, the more sensitive the variable is to the combined effects of multiple parameter changes.

6.3.15 Description of "what if" and SSP scenarios

Table 6.3-3 Description of "what if" and SSP scenarios.

Population	S1	This run simulates the effects of 10% population decrease
	S2	This run simulates the effects of 20% population decrease
	S3	This run simulates the effects of 30% population decrease
	S4	This run simulates the effects of 30% population growth
Consumer price index (CPI)	S5	This run simulates the effects of 30% increase in consumer price index (CPI)
	S6	This run simulates the effects of 50% increase in consumer price index (CPI)
	S7	This run simulates the effects of 30% decrease in consumer price index (CPI)
	S8	This run simulates the effects of 50% decrease in consumer price index (CPI)
Population and consumer price index (CPI)	S9	This run simulates the effects of 20% population decrease, 30% increase in consumer price index (CPI)
	S10	This run simulates the effects of 20% population growth, 30% decrease in consumer price index (CPI)
Temperature (BAU increase 3.24°C: (14.12+3.24=17.36°C))	S11	This run simulates the effects of 1.5°C rise of temperature (14.12+1.5=15.62°C)
	S12	This run simulates the effects of 2.5°C rise of temperature (14.12+2.5=16.62°C)
	S13	This run simulates the effects of 4.6°C rise of temperature (14.12+4.6=18.72°C)
	S14	This run simulates the effects of 5.7°C rise of temperature (14.12+5.7=19.82°C)

Rainfall (BAU decrease to 624mm in 2100, is 90% rainfall in 2020)	S15	80% of rainfall (556.8mm)
	S16	70% of rainfall (487.2mm)
	S17	50% of rainfall (348mm)
	S18	110% of rainfall (765mm)
	S19	150% of rainfall (1044mm)
Temperature and rainfall	S20	This run simulates the effects of 1.5°C rise of temperature (14.12+1.5=15.62°C) and150% of rainfall (1044mm)
	S21	This run simulates the effects of 2.5°C rise of temperature (14.12+2.5=16.62°C) and 110% of rainfall (765mm)
	S22	This run simulates the effects of 4.6°C rise of temperature (14.12+4.6=18.72°C) and 70% of rainfall (487.2mm)
	S23	This run simulates the effects of 5.7°C rise of temperature (14.12+5.7=19.82°C) and 50% of rainfall (348mm)
Water consumption	S24	Water consumption decrease 30%, which caused water cover land increase
	S25	Water consumption increases 30%, which caused water cover land loss
Drought- water saving scenario	S26	Water consumption decreases 30% caused water cover land increase; 5.7°C rise of temperature (14.12+5.7=19.82°C) and 50% of rainfall (348mm)
Drought- large water consumption scenario	S27	Water consumption increases 30% cause water cover land loss; 5.7°C rise of temperature (14.12+5.7=19.82°C) and 50% of rainfall (348mm)

Water abundance - large water consumption scenario	S28	Water consumption increase 30% caused water cover land loss; 1.5°C rise of temperature (14.12+1.5=15.62°C) and 150% of rainfall (1044mm)
Water abundance - water saving scenario	S29	Water consumption decrease 30% cause water cover land increase; 1.5°C rise of temperature (14.12+1.5=15.62°C) and 150% of rainfall (1044mm)
Urbanization rate (BAU-maximum 80% in 2100)	S30	Urbanization rates increase to 92% in 2100
	S31	Urbanization rates increase to 60% in 2100
	S32	Urbanization rates increase to 70% in 2100
Farmland	S33	Annual per capita farmland management growth: 0.003 (BAU (0.0006))
	S34	Annual per capita farmland management growth: 0.005 (BAU (0.0006))
	S35	Annual per capita farmland management growth: 0.0001 (BAU (0.0006))
Grassland	S36	Grassland to construction land: 50 years (BAU-30)
	S37	Grassland to construction land: 20 years (BAU-30)
	S38	Grassland to construction land: 10 years (BAU-30)
Carbon emission	S39	No Carbon emission control
	S40	Carbon emission control Intensity: +40%
	S41	Carbon emission control Intensity: -30%
	S42	Carbon emission control Intensity: -20%
Forestland	S43	Afforestation for carbon sequestration: + 12%, farmland to forest: 20years (BAU-50 years), aesthetic landscape makes forest: 15 years (BAU-20 years);

	S44	Afforestation for carbon sequestration: + 20%, farmland to forest: 10 years (BAU-50 years), aesthetic landscape makes forest: 10 years (BAU-20 years);
	S45	No Afforestation for carbon sequestration, farmland to forest: 70 years (BAU-50 years), aesthetic landscape makes forest: 30 years (BAU-20 years).
Barren land	S46	Barren land to construction land: 20 years (BAU-5)
	S47	Barren land to construction land: 10 years (BAU-5)
	S48	Barren land to construction land: 1 year (BAU-5)
Construction, forest, grassland and farmland	S49	Urbanization rate increase to 70% in 2100 Afforestation for carbon sequestration: + 20%, farmland to forest: 10 years (BAU-50 years), aesthetic landscape makes forest: 10 years (BAU-20 years); Grassland to construction land: 50 years (BAU-30 years) Annual per capita farmland management growth: 0.005 (BAU-0.0006).
	S50	Urbanization rate increase to 92% in 2100 No Afforestation for carbon sequestration, farmland to forest: 70 years (BAU-50 years), aesthetic landscape makes forest: 30 years (BAU-20 years); Grassland to construction land: 10 years (BAU-30 years) Annual per capita farmland management growth: 0.0001 (BAU (0.0006))
Shared Socio-economic Pathways (SSPs).		

Sustainability	SSP1	**Less life stress:** Population: -20%, Urbanization rate: 60%; Consumer price index (CPI): -30% **Better climate situation:** Temperature: +1.5°C, rainfall: +30%; **Strong water-saving regulation:** Water consumption control to 80% to promote water covered land increase **Strong farmland regulation:** Annual per capita farmland management growth: 0.005 (BAU(0.0006)) **Grain to Green program and Green-tourism requirement:** Afforestation for carbon sequestration: + 20%, farmland to forest: 10 years (BAU-50 years), aesthetic landscape makes forest: 10 years (BAU-30 years); **Better grassland and barren land protection:** grassland to construction: 50 years (BAU-30 years); barren land to construction land: 20 years (BAU-5 years); **Carbon emission control** Intensity: +40%
Middle of the road	SSP2	Population: no change, Urbanization rate: no change (BAU: 80%); Consumer price index (CPI): no changeBetter climate situation:Temperature: +3.5°C (BAU: 3.2°C), rainfall: -10%;Medium water-saving regulation: No change of Water consumption and water covered landMedium farmland regulation: Annual per capita farmland management growth: no changeMedium forestland regulation: Afforestation for carbon sequestration: no change, farmland to forest: 40 years (BAU-50 years), aesthetic landscape makes forest: 15 years (BAU-

		20 years);Limited grassland regulation: grassland to construction: no change (BAU-30 years);Limited barrenland regulation: barren land to construction land: 10 years (BAU-5 years);Limited carbon emission control Intensity: no change
Regional rivalry pathway	SSP3	**Bad social-economy background:** Population: +30%, Urbanization rate: 60%; Consumer price index (CPI): +50% **Bad climate situation:** 4.6°C rise of temperature (14.12+4.6=18.72°C) and 70% of rainfall (487.2mm) **Huge water press:** Less water-saving regulation: Water consumption increase 20%, makes water covered land loss. **Limited farmland support:** Annual per capita farmland management growth: 0.005 (BAU-0.0006) **Limited forestland strategy:** Afforestation for carbon sequestration: - 20%, farmland to forest: 70 years (BAU-50 years), aesthetic landscape makes forest: 40 years (BAU-20 years); **Constructed land emcroached Grassland and barren land:** grassland to construction: 10 years (BAU-30 years); barren land to construction land: 1 years (BAU-5 years); **Limited carbon emission control Intensity**: -30%

Inequality	SSP4	**Inequal social-economy background:** Population: +20%, Urbanization rate: 70%; Consumer price index (CPI): +30% **Better climate situation:**4.6°C rise of temperature (14.12+4.6=18.72°C) and 80% of rainfall **Less vs more water-saving regulation:** Water consumption increase 10%, makes water covered land loss. **Good vs bad farmland support:** Annual per capita farmland management growth: 0.001 (BAU-0.0006) **Good vs bad forestland regulation:** Afforestation for carbon sequestration: + 10%, farmland to forest: 40 years (BAU-50 years), aesthetic landscape makes forest: 15 years (BAU-20 years); Limited grassland regulation: grassland to construction: 20 years (BAU-30 years); Limited barrenland regulation: barren land to construction land: 3 years (BAU-5 years); **Limited carbon emission control** Intensity: +20%
Fossil-fueled development	SSP5	Better social-economic environment: Population: +5%, Urbanization rate: 92%; Consumer price index (CPI): -50% The heaviest drought situation: Temperature: 5.7°C rise of temperature (14.12+5.7=19.82°C) and 50% of rainfall (348mm) More water requirment: Water consumption increase 30%, makes water covered land loss. Better farm management tech: Annual per capita farmland management growth: 0.005

		(BAU(0.0006)) No afforestration strategy: No Afforestation for carbon sequestration, farmland to forest: 70 years (BAU-50 years), aesthetic landscape makes forest: 30 years (BAU-20 years). Constructed land emcroached Grassland and barren land: grassland to construction: 10 years (BAU-30 years); barren land to construction land: 1 years (BAU-5 years); No carbon emission regulation: No Carbon emission control

Reference

Alfthan, B., Gjerdi, H., Puikkonen, L., Schoolmeester, T., Andresen, M., Gjerdi, H. L., Jurek, M., & Semernya, L. (2018). *Mountain Adaptation Outlook Series: Synthesis Report*.

Alhakimi, S. S. (2018). Export and economic growth in Saudi Arabia: The granger causality test. *Asian Journal of Economics and Empirical Research*, *5*(1), 29–35. https://doi.org/10.20448/journal.501.2018.51.29.35

Anees, M. M., Sharma, R., & Joshi, P. K. (2022). Urbanization in Himalaya—An Interregional Perspective to Land Use and Urban Growth Dynamics. In U. Schickhoff, R. B. Singh, & S. Mal (Eds), *Mountain Landscapes in Transition: Effects of Land Use and Climate Change* (pp. 517–538). Springer International Publishing. https://doi.org/10.1007/978-3-030-70238-0_23

Averis, A., & Pearson, A. (2003). Filling the gaps: Identifying nursing research priorities through the analysis of completed systematic reviews. *Jbi Reports*, *1*(3), 49–126. https://doi.org/10.1046/j.1479-6988.2003.00003.x

Badamfirooz, J., Mousazadeh, R., & Sarkheil, H. (2021). A proposed framework for economic valuation and assessment of damages cost to national wetlands ecosystem services using the benefit-transfer approach. *Environmental Challenges*, *5*, 100303. https://doi.org/10.1016/j.envc.2021.100303

Barlas, Y. (1989). Multiple tests for validation of system dynamics type of simulation models. *European Journal of Operational Research*, *42*(1), 59–87.

Barlas, Y. (1996). Formal aspects of model validity and validation in system dynamics. *System Dynamics Review: The Journal of the System Dynamics Society*, *12*(3), 183–210.

Basak, S. M., Hossain, M. S., Tusznio, J., & Grodzińska-Jurczak, M. (2021). Social benefits of river restoration from ecosystem services perspective: A systematic review. *Environmental Science & Policy*, *124*, 90–100. https://doi.org/10.1016/j.envsci.2021.06.005

Bastan, M., Khorshid-Doust, R. R., Sisi, S. D., & Ahmadvand, A. (2017). Sustainable development of agriculture: A system dynamics model. *Kybernetes*, *47*(1), 142–162.

Bathiany, S., Bastiaansen, R., Bastos, A., Blaschke, L., Lever, J., Loriani, S., De Keersmaecker, W., Dorigo, W., Milenković, M., Senf, C., Smith, T., Verbesselt, J., & Boers, N. (2024). Ecosystem Resilience Monitoring and Early Warning Using Earth Observation Data: Challenges and Outlook. *Surveys in Geophysics*. https://doi.org/10.1007/s10712-024-09833-z

Belay, T., Melese, T., & Senamaw, A. (2022). Impacts of land use and land cover change on ecosystem service values in the Afroalpine area of Guna Mountain, Northwest Ethiopia. *Heliyon*, *8*(12). https://doi.org/10.1016/j.heliyon.2022.e12246

Bennett, E. M., Cramer, W., Begossi, A., Cundill, G., Díaz, S., Egoh, B. N., Geijzendorffer, I. R., Krug, C. B., Lavorel, S., Lazos, E., Lebel, L., Martín-López, B., Meyfroidt, P., Mooney, H. A., Nel, J. L., Pascual, U., Payet, K., Harguindeguy, N. P., Peterson, G. D., … Woodward, G. (2015). Linking biodiversity, ecosystem services, and human well-being: Three challenges for designing research for sustainability. *Current Opinion in Environmental Sustainability*, *14*, 76–85. https://doi.org/10.1016/j.cosust.2015.03.007

Berrio-Giraldo, L., Villegas-Palacio, C., & Arango-Aramburo, S. (2021). Understating complex interactions in socio-ecological systems using system dynamics: A case in the tropical Andes. *Journal of Environmental Management*, *291*, 112675. https://doi.org/10.1016/j.jenvman.2021.112675

Biggs, R., Preiser, R., De Vos, A., Schlüter, M., Maciejewski, K., & Clements, H. (2021). *The Routledge Handbook of Research Methods for Social-Ecological Systems* (1st edn). Routledge. https://doi.org/10.4324/9781003021339

Billio, M., Getmansky, M., Lo, A. W., & Pelizzon, L. (2012). Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics*, *104*(3), 535–559. https://doi.org/10.1016/j.jfineco.2011.12.010

Boakes, E. H., Dalin, C., Etard, A., & Newbold, T. (2024). Impacts of the global food system on terrestrial biodiversity from land use and climate change. *Nature Communications*, *15*(1), 5750. https://doi.org/10.1038/s41467-024-49999-z

Boerema, A., Rebelo, A. J., Bodi, M. B., Esler, K. J., & Meire, P. (2017). Are ecosystem services adequately quantified? *Journal of Applied Ecology*, *54*(2), 358–370. https://doi.org/10.1111/1365-2664.12696

Bogdan, S.-M., Pătru-Stupariu, I., & Zaharia, L. (2016). The assessment of regulatory ecosystem services: The case of the sediment retention service in a mountain landscape in the Southern Romanian Carpathians. *Procedia Environmental Sciences*, *32*, 12–27.

Cabernard, L., Pfister, S., & Hellweg, S. (2024). Biodiversity impacts of recent land-use change driven by increases in agri-food imports. *Nature Sustainability*, *7*(11), 1512–1524. https://doi.org/10.1038/s41893-024-01433-4

Canedoli, C., Rota, N., Vogiatzakis, I. N., Zanchi, A., Drius, M., Nagendra, H., & Padoa-Schioppa, E. (2024). Review of indicators for mountain ecosystem services: Are the most frequently used also the best? *Ecological Indicators*, *166*, 112310. https://doi.org/10.1016/j.ecolind.2024.112310

Cao, Y., Kong, L., Zhang, L., & Ouyang, Z. (2021). The balance between economic development and ecosystem service value in the process of land urbanization: A case study of China’s land urbanization from 2000 to 2015. *Land Use Policy*, *108*, 105536. https://doi.org/10.1016/j.landusepol.2021.105536

Carroll, C., & Noss, R. F. (2021). Rewilding in the face of climate change. *Conservation Biology*, *35*(1), 155–167. https://doi.org/10.1111/cobi.13531

Chen, T., Feng, Z., Zhao, H., & Wu, K. (2020). Identification of ecosystem service bundles and driving factors in Beijing and its surrounding areas. *Science of The Total Environment*, *711*. https://doi.org/10.1016/j.scitotenv.2019.134687

Chen, W., & Chi, G. (2022). Urbanization and ecosystem services: The multi-scale spatial spillover effects and spatial variations. *Land Use Policy*, *114*, 105964. https://doi.org/10.1016/j.landusepol.2021.105964

Cheng, K., Yang, H., Tao, S., Su, Y., Guan, H., Ren, Y., Hu, T., Li, W., Xu, G., Chen, M., Lu, X., Yang, Z., Tang, Y., Ma, K., Fang, J., & Guo, Q. (2024). Carbon storage through China's planted forest expansion. *Nature Communications*, *15*(1), 4106. https://doi.org/10.1038/s41467-024-48546-0

China Statistical Yearbook. (1999). [Data set]. https://www.stats.gov.cn/sj/ndsj/

Chowdhury, M., Hasan, M. E., & Abdullah-Al-Mamun, M. M. (2020). Land use/land cover change assessment of Halda watershed using remote sensing and GIS. *The Egyptian Journal of Remote Sensing and Space Science*, *23*(1), 63–75. https://doi.org/10.1016/j.ejrs.2018.11.003

CICES. (2011). Common International Classification of Ecosystem Services (CICES). *European Environment Agency: Copenhagen, Denmark*, *33*, 107.

Coban, O., De Deyn, G. B., & Van Der Ploeg, M. (2022). Soil microbiota as game-changers in restoration of degraded lands. *Science*, *375*(6584), abe0725. https://doi.org/10.1126/science.abe0725

Colglazier, W. (2015). Sustainable development agenda: 2030. *Science*, *349*(6252), 1048–1050. https://doi.org/10.1126/science.aad2333

Cooper, G. (2018). *Social-ecological tipping points in world deltas: Designing a safe and just operating space for the Chilika lagoon fishery, India* [Phd, University of Southampton]. https://eprints.soton.ac.uk/421929/

Costanza, R., d'Arge, R., de Groot, R., Farber, S., Grasso, M., Hannon, B., Limburg, K., Naeem, S., O'Neill, R. V., Paruelo, J., Raskin, R. G., Sutton, P., & van den Belt, M. (1997). The value of the world's ecosystem services and natural capital. *Nature*, *387*(6630), 253–260. https://doi.org/10.1038/387253a0

Dai, E., Yin, L., Wang, Y., Ma, L., & Tong, M. (2020). Quantitative Assessment of the Relative Impacts of Land Use and Climate Change on the Key Ecosystem Services in the Hengduan Mountain Region, China. *Sustainability*, *12*(10), Article 10. https://doi.org/10.3390/su12104100

Dax, T., Schroll, K., Machold, I., Derszniak-Noirjean, M., Schuh, B., & Gaupp-Berghausen, M. (2021). Land Abandonment in Mountain Areas of the EU: An Inevitable Side Effect of Farming Modernization and Neglected Threat to Sustainable Land Use. *Land*, *10*(6), Article 6. https://doi.org/10.3390/land10060591

De Araujo Barbosa, C. C., Atkinson, P. M., & Dearing, J. A. (2016). Extravagance in the commons: Resource exploitation and the frontiers of ecosystem service depletion in the Amazon estuary. *Science of The Total Environment*, *550*, 6–16. https://doi.org/10.1016/j.scitotenv.2016.01.072

Dearing, J. A., Wang, R., Zhang, K., Dyke, J. G., Haberl, H., Hossain, M. S., Langdon, P. G., Lenton, T. M., Raworth, K., & Brown, S. (2014). Safe and just operating spaces for regional social-ecological systems. *Global Environmental Change*, *28*, 227–238. https://doi.org/10.1016/j.gloenvcha.2014.06.012

Dearing, J. A., Wang, R., Zhang, K., Dyke, J. G., Haberl, H., Hossain, Md. S., Langdon, P. G., Lenton, T. M., Raworth, K., Brown, S., Carstensen, J., Cole, M. J., Cornell, S. E., Dawson, T. P., Doncaster, C. P., Eigenbrod, F., Flörke, M., Jeffers, E., Mackay, A. W., … Poppy, G. M. (2014a). Safe and just operating spaces for regional social-ecological systems. *Global Environmental Change*, *28*, 227–238. https://doi.org/10.1016/j.gloenvcha.2014.06.012

Dearing, J. A., Wang, R., Zhang, K., Dyke, J. G., Haberl, H., Hossain, Md. S., Langdon, P. G., Lenton, T. M., Raworth, K., Brown, S., Carstensen, J., Cole, M. J., Cornell, S. E., Dawson, T. P., Doncaster, C. P., Eigenbrod, F., Flörke, M., Jeffers, E., Mackay, A. W., … Poppy, G. M. (2014b). Safe and just operating spaces for regional social-ecological systems. *Global Environmental Change*, *28*, 227–238. https://doi.org/10.1016/j.gloenvcha.2014.06.012

Deeksha, Shukla, A. K., Rama Devi, N., & Shukla, S. (2023). Remote Sensing and Its Application on Soil: An Ecosystem Services. In M. Pandey, A. K. Gupta, & G. Oliveto (Eds), *River, Sediment and Hydrological Extremes: Causes, Impacts and Management* (pp. 307–319). Springer Nature. https://doi.org/10.1007/978-981-99-4811-6_17

Deng, C., Liu, J., Nie, X., Li, Z., Liu, Y., Xiao, H., Hu, X., Wang, L., Zhang, Y., Zhang, G., Zhu, D., & Xiao, L. (2021). How trade-offs between ecological construction and urbanization expansion affect ecosystem services. *Ecological Indicators*, *122*, 107253. https://doi.org/10.1016/j.ecolind.2020.107253

Dinda, S. (2004, January). *Environmental Kuznets Curve: An Envelope of Technological Progress* [MPRA Paper]. https://mpra.ub.uni-muenchen.de/28092/

Duan, Y., Di, B., Ustin, S. L., Xu, C., Xie, Q., Wu, S., Li, J., & Zhang, R. (2021). Changes in ecosystem services in a montane landscape impacted by major earthquakes: A case study in Wenchuan earthquake-affected area, China. *Ecological Indicators*, *126*. https://doi.org/10.1016/j.ecolind.2021.107683

Egger, M. (2001). *Rationale, potentials, and promise of systematic reviews. S. 3–19 in: Mathias Egger, George Davey Smith und Douglas G. Altman (Hg.): Systematic Reviews in Health Care. Meta-analysis in context*. London: BMJ Publishing Group.

El-Bilali, H., Bassole, I. H. N., Dambo, L., & Berjan, S. (2020). *Climate change and food security.* https://doi.org/10.17707/AgricultForest.66.3.16

Estes, L., Elsen, P. R., Treuer, T., Ahmed, L., Caylor, K., Chang, J., Choi, J. J., & Ellis, E. C. (2018). The spatial and temporal domains of modern ecology. *Nature Ecology & Evolution*, *2*(5), 819–826. https://doi.org/10.1038/s41559-018-0524-4

Estoque, R. C. (2023). Complexity and diversity of nexuses: A review of the nexus approach in the sustainability context. *Science of The Total Environment*, *854*, 158612. https://doi.org/10.1016/j.scitotenv.2022.158612

Eswaran, H., Lal, R., & Reich, P. (2019). Land degradation: An overview. *Response to Land Degradation*, 20–35.

Evangelista, V., Scariot, A., Teixeira, H. M., & Júnior, I. M. L. (2024). Local ecological knowledge and perception as a strategy in the management of ecosystem services. *Journal of Environmental Management*, *368*, 122095. https://doi.org/10.1016/j.jenvman.2024.122095

Evans, D. L., Falagán, N., Hardman, C. A., Kourmpetli, S., Liu, L., Mead, B. R., & Davies, J. A. C. (2022). Ecosystem service delivery by urban agriculture and green infrastructure – a systematic review. *Ecosystem Services*, *54*, 101405. https://doi.org/10.1016/j.ecoser.2022.101405

Fan, M., Chen, L., & Wang, Q. (2019). Assessing the high impacts of land use change: Spatial characteristics of land uses and ecological compensation based on payment for ecosystem services model in a mountainous area, China. *Mitigation and Itigation and Adaptation Strategies For Global Change*, *24*(8), 1431–1460. https://doi.org/10.1007/s11027-019-09858-5

Fan, M., & Xiao, Y. (2020). Impacts of the grain for Green Program on the spatial pattern of land uses and ecosystem services in mountainous settlements in southwest China. *Global Ecology and Convervation*, *21*. https://doi.org/10.1016/j.gecco.2019.e00806

Fang, Z., Ding, T., Chen, J., Xue, S., Zhou, Q., Wang, Y., Wang, Y., Huang, Z., & Yang, S. (2022a). Impacts of land use/land cover changes on ecosystem services in ecologically fragile regions. *Science of The Total Environment*, *831*, 154967. https://doi.org/10.1016/j.scitotenv.2022.154967

Fang, Z., Ding, T., Chen, J., Xue, S., Zhou, Q., Wang, Y., Wang, Y., Huang, Z., & Yang, S. (2022b). Impacts of land use/land cover changes on ecosystem services in ecologically fragile regions. *Science of The Total Environment*, *831*, 154967. https://doi.org/10.1016/j.scitotenv.2022.154967

Fang, Z., Ding, T., Chen, J., Xue, S., Zhou, Q., Wang, Y., Wang, Y., Huang, Z., & Yang, S. (2022c). Impacts of land use/land cover changes on ecosystem services in ecologically fragile regions. *Science of The Total Environment*, *831*, 154967. https://doi.org/10.1016/j.scitotenv.2022.154967

Felipe-Lucia, M. R., Guerrero, A. M., Alexander, S. M., Ashander, J., Baggio, J. A., Barnes, M. L., Bodin, Ö., Bonn, A., Fortin, M.-J., Friedman, R. S., Gephart, J. A., Helmstedt, K. J., Keyes, A. A., Kroetz, K., Massol, F., Pocock, M. J. O., Sayles, J., Thompson, R. M., Wood, S. A., & Dee, L. E. (2022). Conceptualizing ecosystem services using social–ecological networks. *Trends in Ecology & Evolution*, *37*(3), 211–222. https://doi.org/10.1016/j.tree.2021.11.012

Foggin, J. M. (2016). *Conservation issues: Mountain ecosystems*. https://doi.org/10.1016/B978-0-12-409548-9.09199-5

Ford, A. (2010). *Modeling the environment* (Vol. 488). Island press Washington, DC.

Fu, B., Zhang, L., Xu, Z., Zhao, Y., Wei, Y., & Skinner, D. (2015a). Ecosystem services in changing land use. *Journal of Soils and Sediments*, *15*(4), 833–843. https://doi.org/10.1007/s11368-015-1082-x

Fu, B., Zhang, L., Xu, Z., Zhao, Y., Wei, Y., & Skinner, D. (2015b). Ecosystem services in changing land use. *Journal of Soils and Sediments*, *15*(4), 833–843. https://doi.org/10.1007/s11368-015-1082-x

Fu, M., Guo, B., Wang, W., Wang, J., Zhao, L., & Wang, J. (2019). Comprehensive Assessment of Water Footprints and Water Scarcity Pressure for Main Crops in Shandong Province, China. *Sustainability*, *11*(7), Article 7. https://doi.org/10.3390/su11071856

Fu, Q., Li, B., Hou, Y., Bi, X., & Zhang, X. (2017). Effects of land use and climate change on ecosystem services in Central Asia's arid regions: A case study in Altay Prefecture, China. *Science of The Total Environment*, *607*, 633–646. https://doi.org/10.1016/j.scitotenv.2017.06.241

Fürst, C., Luque, S., & Geneletti, D. (2017). Nexus thinking – how ecosystem services can contribute to enhancing the cross-scale and cross-sectoral coherence between land use, spatial planning and policy-making. *International Journal of Biodiversity Science, Ecosystem Services & Management*, *13*(1), 412–421. https://doi.org/10.1080/21513732.2017.1396257

Gao, H., Zhang, C., & Wang, H. (2014). Impact of grain for green project on ecosystem servicevalues in Karst mountains (Chinese). *Journal of Guizhou Normal University (Natural Sciences)*, *Vol. 32*(No. 6), 25–28.

Gao, J., Bian, H., Zhu, C., & Tang, S. (2022). The response of key ecosystem services to land use and climate change in Chongqing: Time, space, and altitude. *Journal of Geographical Sciences*, *32*(2), 317–332. https://doi.org/10.1007/s11442-022-1949-x

Gao, J., Tang, X., Lin, S., & Bian, H. (2021). The Influence of Land Use Change on Key Ecosystem Services and Their Relationships in a Mountain Region from Past to Future (1995-2050). *Forests*, *12*(5). https://doi.org/10.3390/f12050616

Gao, J., Zuo, L., & Liu, W. (2021). Environmental determinants impacting the spatial heterogeneity of karst ecosystem services in Southwest China. *Land Degradation & Development*, *32*(4), 1718–1731. https://doi.org/10.1002/ldr.3815

Gao, X., Huang, B., Hou, Y., Xu, W., Zheng, H., Ma, D., & Ouyang, Z. (2020). Using Ecosystem Service Flows to Inform Ecological Compensation: Theory & Application. *International Journal of Environmental Research and Public Health*, *17*(9), Article 9. https://doi.org/10.3390/ijerph17093340

García-Díez, V., García-Llorente, M., & González, J. A. (2020). Participatory Mapping of Cultural Ecosystem Services in Madrid: Insights for Landscape Planning. *Land*, *9*(8), Article 8. https://doi.org/10.3390/land9080244

Goldstein, J. H., Caldarone, G., Duarte, T. K., Ennaanay, D., Hannahs, N., Mendoza, G., Polasky, S., Wolny, S., & Daily, G. C. (2012). Integrating ecosystem-service tradeoffs into land-use decisions. *Proceedings of the National Academy of Sciences*, *109*(19), 7565–7570. https://doi.org/10.1073/pnas.1201040109

Gomes, E., Inácio, M., Bogdzevič, K., Kalinauskas, M., Karnauskaitė, D., & Pereira, P. (2021). Future land-use changes and its impacts on terrestrial ecosystem services: A review. *Science of The Total Environment*, *781*, 146716. https://doi.org/10.1016/j.scitotenv.2021.146716

Gomez-Jaramillo, Y., Berrouet, L., Villegas-Palacio, C., & Berrio-Giraldo, L. (2024). Conceptual framework for analyzing the sustainability of socio-ecological systems with a focus on ecosystem services that support water security. *Sustainable Development*, *32*(3), 2298–2313. https://doi.org/10.1002/sd.2780

Gong, J., Cao, E., Xie, Y., Xu, C., Li, H., & Yan, L. (2021). Integrating ecosystem services and landscape ecological risk into adaptive management: Insights from a western mountain-basin area, China. *Journal of Environmental Management*, *281*. https://doi.org/10.1016/j.jenvman.2020.111817

Gong, J., Liu, D., Zhang, J., Xie, Y., Cao, E., & Li, H. (2019). Tradeoffs/synergies of multiple ecosystem services based on land use simulation in a mountain-basin area, western China. *Ecological Indicators*, *99*, 283–293. https://doi.org/10.1016/j.ecolind.2018.12.027

Gong, J., Xie, Y., Cao, E., Huang, Q., & Li, H. (2019). Integration of InVEST-habitat quality model with landscape pattern indexes to assess mountain plant biodiversity change: A case study of Bailongjiang watershed in Gansu Province. *Journal of Geographical Sciences*, *29*(7), 1193–1210. https://doi.org/10.1007/s11442-019-1653-7

Gottwald, S., Albert, C., & Fagerholm, N. (2022). Combining sense of place theory with the ecosystem services concept: Empirical insights and reflections from a participatory mapping study. *Landscape Ecology*, *37*(2), 633–655. https://doi.org/10.1007/s10980-021-01362-z

Grafius, D. R., Corstanje, R., Warren, P. H., Evans, K. L., Hancock, S., & Harris, J. A. (2016). The impact of land use/land cover scale on modelling urban ecosystem services. *Landscape Ecology*, *31*(7), 1509–1522. https://doi.org/10.1007/s10980-015-0337-7

Green, S., Higgins, J., Alderson, P., Clarke, M., Mulrow, C. D., & Oxman, A. D. (2008). *Cochrane handbook for systematic reviews of interventions. West Sussex, England*. John Wiley & Sons Ltd.

Grêt-Regamey, A., Brunner, S. H., & Kienast, F. (2012). Mountain ecosystem services: Who cares? *Mountain Research and Development*, *32*(S1). https://doi.org/10.1659/MRD-JOURNAL-D-10-00115.S1

Gross, J., & Ouyang, Y. (2021). Types of urbanization and economic growth. *International Journal of Urban Sciences*, *25*(1), 71–85. https://doi.org/10.1080/12265934.2020.1759447

Guo, C., Gao, S., & Zhou, B. (2019). Study on the impact of land use change on ecological service value in Funiu Mountain based on grid (Chinese). *Acta Ecologica Sinica.*

Guo, H., He, S., Jing, H., Yan, G., & Li, H. (2023). Evaluation of the Impacts of Change in Land Use/Cover on Carbon Storage in Multiple Scenarios in the Taihang Mountains, China. *Sustainability*, *15*(19). https://doi.org/10.3390/su151914244

Guo, W., Wang, R., & Meng, F. (2024a). Simulation and Forecast of Coastal Ecosystem Services in Jiaodong Peninsula Based on SSP-RCP Scenarios. *Remote Sensing*, *16*(19), Article 19. https://doi.org/10.3390/rs16193614

Guo, W., Wang, R., & Meng, F. (2024b). Simulation and Forecast of Coastal Ecosystem Services in Jiaodong Peninsula Based on SSP-RCP Scenarios. *Remote Sensing*, *16*(19), Article 19. https://doi.org/10.3390/rs16193614

Haddaway, N. R., Macura, B., Whaley, P., & Pullin, A. S. (2018). ROSES RepOrting standards for Systematic Evidence Syntheses: Pro forma, flow-diagram and descriptive summary of the plan and conduct of environmental systematic reviews and systematic maps. *Environmental Evidence*, *7*, 1–8. https://doi.org/10.1186/s13750-018-0121-7

Haida, C., Rüdisser, J., & Tappeiner, U. (2016). Ecosystem services in mountain regions: Experts' perceptions and research intensity. *Regional Environmental Change*, *16*(7), 1989–2004. https://doi.org/10.1007/s10113-015-0759-4

Haque, Md. N., & Sharifi, A. (2024). Who are marginalized in accessing urban ecosystem services? A systematic literature review. *Land Use Policy*, *144*, 107266. https://doi.org/10.1016/j.landusepol.2024.107266

Haraldsson, H. V. (2004). *Introduction to system thinking and causal loop diagrams*. Department of chemical engineering, Lund University Lund, Sweden.

He, Q., Bertness, M. D., Bruno, J. F., Li, B., Chen, G., Coverdale, T. C., Altieri, A. H., Bai, J., Sun, T., Pennings, S. C., Liu, J., Ehrlich, P. R., & Cui, B. (2014). Economic development and coastal ecosystem change in China. *Scientific Reports*, *4*(1), 5995. https://doi.org/10.1038/srep05995

He, Y., Lee, E., & Warner, T. A. (2017). A time series of annual land use and land cover maps of China from 1982 to 2013 generated using AVHRR GIMMS NDVI3g data. *Remote Sensing of Environment*, *199*, 201–217. https://doi.org/10.1016/j.rse.2017.07.010

Hossain, M. S., Dearing, J. A., Eigenbrod, F., & Johnson, F. A. (2017). Operationalizing safe operating space for regional social-ecological systems. *Science* *of the Total Environment*, *584*, 673–682. https://doi.org/10.1016/j.scitotenv.2017.01.095

Hossain, M. S., Ramirez, J., Szabo, S., Eigenbrod, F., Johnson, F. A., Speranza, C. I., & Dearing, J. A. (2020). Participatory modelling for conceptualizing social-ecological system dynamics in the Bangladesh delta. *Regional Environmental Change*, *20*(1), 28. https://doi.org/10.1007/s10113-020-01599-5

Hou, D., Meng, F., & Prishchepov, A. V. (2021). How is urbanization shaping agricultural land-use? Unraveling the nexus between farmland abandonment and urbanization in China. *Landscape and Urban Planning*, *214*, 104170. https://doi.org/10.1016/j.landurbplan.2021.104170

Hua, Z., Ma, J., Sun, Y., Yang, Y., Zhu, X., & Chen, F. (2024). Multi-Scenario Simulating the Impacts of Land Use Changes on Ecosystem Health in Urban Agglomerations on the Northern Slope of the Tianshan Mountain, China. *Land*, *13*(5), Article 5. https://doi.org/10.3390/land13050571

Huang, A., Xu, Y., Sun, P., Zhou, G., Liu, C., Lu, L., Xiang, Y., & Wang, H. (2019). Land use/land cover changes and its impact on ecosystem services in ecologically fragile zone: A case study of Zhangjiakou City, Hebei Province, China. *Ecological Indicators*, *104*, 604–614. https://doi.org/10.1016/j.ecolind.2019.05.027

Huang, J., Hu, Y., & Zheng, F. (2020). Research on recognition and protection of ecological security patterns based on circuit theory: A case study of Jinan City. *Environmental Science and Pollution Research*, *27*(11), 12414–12427. https://doi.org/10.1007/s11356-020-07764-x

Huang, Q., Sun, H., Wang, R., & Zhang, H. (2007). The effect of oasis land use/coverage on the value of the service value in the oasis—Desert system (Chinese). *Journal of Desert Research*.

Huang, S., Xiao, X., Tian, T., & Che, Y. (2024). Seasonal influences on preferences for urban blue-green spaces: Integrating land surface temperature into the assessment of cultural ecosystem service value. *Sustainable Cities and Society*, *102*, 105237. https://doi.org/10.1016/j.scs.2024.105237

Immerzeel, W. W., Lutz, A. F., Andrade, M., Bahl, A., Biemans, H., Bolch, T., Hyde, S., Brumby, S., Davies, B. J., Elmore, A. C., Emmer, A., Feng, M., Fernández, A., Haritashya, U., Kargel, J. S., Koppes, M., Kraaijenbrink, P. D. A., Kulkarni, A. V., Mayewski, P. A., … Baillie, J. E. M. (2020). Importance and vulnerability of the world's water towers. *Nature*, *577*(7790), 364–369. https://doi.org/10.1038/s41586-019-1822-y

IPBES. (2019a). *Global assessment report on biodiversity and ecosystem services of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services*. Zenodo. https://doi.org/10.5281/zenodo.6417333

IPBES. (2019b). *Global assessment report on biodiversity and ecosystem services of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services* (p. 1148). IPBES Bonn, Germany.

IPCC, Geneva, Switzerland, Xiaona, Y., Wangqiang, Z., & Wei, L. (2021). *AR6 climate change 2021: The physical science basis*.

Iversen, E. K., Grimsrud, K., Lindhjem, H., & Navrud, S. (2024). Mountains of trouble: Accounting for environmental costs of land use change from tourism development. *Tourism Management*, *102*, 104870. https://doi.org/10.1016/j.tourman.2023.104870

Jay, W. F. (1961). Industrial Dynamics. *Waltham MA, Pegasus Communications*.

Jeon, C., & Shin, J. (2014). Long-term renewable energy technology valuation using system dynamics and Monte Carlo simulation: Photovoltaic technology case. *Energy*, *66*, 447–457. https://doi.org/10.1016/j.energy.2014.01.050

Jia, Q., Jiao, L., Lian, X., & Wang, W. (2023). Linking supply-demand balance of ecosystem services to identify ecological security patterns in urban agglomerations. *Sustainable Cities and Society*, *92*, 104497. https://doi.org/10.1016/j.scs.2023.104497

Jiang, L., Wang, Z., Zuo, Q., & Du, H. (2023a). Simulating the impact of land use change on ecosystem services in agricultural production areas with multiple scenarios considering ecosystem service richness. *Journal of Cleaner Production*, *397*, 136485. https://doi.org/10.1016/j.jclepro.2023.136485

Jiang, L., Wang, Z., Zuo, Q., & Du, H. (2023b). Simulating the impact of land use change on ecosystem services in agricultural production areas with multiple scenarios considering ecosystem service richness. *Journal of Cleaner Production*, *397*, 136485. https://doi.org/10.1016/j.jclepro.2023.136485

Jiang, W., Wu, T., & Fu, B. (2021). The value of ecosystem services in China: A systematic review for twenty years. *Ecosystem Services*, *52*, 101365. https://doi.org/10.1016/j.ecoser.2021.101365

Johnson, J. A., Ruta, G., Baldos, U., Cervigni, R., Chonabayashi, S., Corong, E., Gavryliuk, O., Gerber, J., Hertel, T., & Nootenboom, C. (2021). *The Economic Case for Nature: A global Earth-economy model to assess development policy pathways*. World Bank.

Kallis, G., & Norgaard, R. B. (2010). Coevolutionary ecological economics. *Ecological Economics*, *69*(4), 690–699. https://doi.org/10.1016/j.ecolecon.2009.09.017

Kim, J., & Son, Y. (2021). Assessing and mapping cultural ecosystem services of an urban forest based on narratives from blog posts. *Ecological Indicators*, *129*, 107983. https://doi.org/10.1016/j.ecolind.2021.107983

Kosanic, A., & Petzold, J. (2020). A systematic review of cultural ecosystem services and human wellbeing. *Ecosystem Services*, *45*, 101168. https://doi.org/10.1016/j.ecoser.2020.101168

Kotir, J. H., Smith, C., Brown, G., Marshall, N., & Johnstone, R. (2016). A system dynamics simulation model for sustainable water resources management and agricultural development in the Volta River Basin, Ghana. *Science of The Total Environment*, *573*, 444–457. https://doi.org/10.1016/j.scitotenv.2016.08.081

Lal, R., Smith ,Pete, Jungkunst ,Hermann F., Mitsch ,William J., Lehmann ,Johannes, Nair ,P.K. Ramachandran, McBratney ,Alex B., de Moraes Sá ,João Carlos, Schneider ,Julia, Zinn ,Yuri L., Skorupa ,Alba L.A., Zhang ,Hai-Lin, Minasny ,Budiman, Srinivasrao ,Cherukumalli, & and Ravindranath, N. H. (2018). The carbon sequestration potential of terrestrial ecosystems. *Journal of Soil and Water Conservation*, *73*(6), 145A-152A. https://doi.org/10.2489/jswc.73.6.145A

Lavorel, S., Anquetin, S., & Buclet, N. (2023). Trajectories of socio-ecological change in mountains. *Regional Environmental Change*, *23*(2), 73. https://doi.org/10.1007/s10113-023-02063-w

Lawler, J. J., Lewis, D. J., Nelson, E., Plantinga, A. J., Polasky, S., Withey, J. C., Helmers, D. P., Martinuzzi, S., Pennington, D., & Radeloff, V. C. (2014). Projected land-use change impacts on ecosystem services in the United States. *Proceedings of the National Academy of Sciences*, *111*(20), 7492–7497. https://doi.org/10.1073/pnas.1405557111

Le Provost, G., Schenk, N. V., Penone, C., Thiele, J., Westphal, C., Allan, E., Ayasse, M., Blüthgen, N., Boeddinghaus, R. S., Boesing, A. L., Bolliger, R., Busch, V., Fischer, M., Gossner, M. M., Hölzel, N., Jung, K., Kandeler, E., Klaus, V. H., Kleinebecker, T., … Manning, P. (2023). The supply of multiple ecosystem services requires biodiversity across spatial scales. *Nature Ecology & Evolution*, *7*(2), 236–249. https://doi.org/10.1038/s41559-022-01918-5

Li, C., Pan, Y., Yin, W., & Lan, S. (2025). Spatial distribution and influencing factors of rural cultural ecosystem services: A case study of Fujian, China. *Scientific Reports*, *15*(1), 10510. https://doi.org/10.1038/s41598-025-95600-y

Li, C., Wu, Y., Gao, B., Zheng, K., Wu, Y., & Li, C. (2021). Multi-scenario simulation of ecosystem service value for optimization of land use in the Sichuan-

Yunnan ecological barrier, China. *Ecological Indicators*, *132*, 108328. https://doi.org/10.1016/j.ecolind.2021.108328

Li, G., & Cai, J. (2022). Spatial and Temporal Differentiation of Mountain Ecosystem Service Trade-Offs and Synergies: A Case Study of Jieshi Mountain, China. *Sustainability*, *14*(8), Article 8. https://doi.org/10.3390/su14084652

Li, J., Cui, L., Miao, D., & Ali, A. (2021). Water resources allocation model based on ecological priority in the arid region. *Environmental Research*, *199*, 111201. https://doi.org/10.1016/j.envres.2021.111201

Li, K., Zhang, L., Chen, B., Zuo, J., Yang, F., & Li, L. (2023). Analysis of China's coastline changes during 1990–2020. *Remote Sensing*, *15*(4), 981.

Li, Q., Zhou, Y., & Yi, S. (2022). An integrated approach to constructing ecological security patterns and identifying ecological restoration and protection areas: A case study of Jingmen, China. *Ecological Indicators*, *137*. https://doi.org/10.1016/j.ecolind.2022.108723

Li, R., Chen, J., Yang, X., Yin, S., Shi, R., Bai, Y., & Xu, L. (2024). The impact of population change on social-ecological systems' vulnerability: A case of the Qinling-Daba Mountains of Southern Shaanxi in China. *Journal of Cleaner Production*, *476*, 143682. https://doi.org/10.1016/j.jclepro.2024.143682

Li, R., Zheng, H., O'Connor, P., Xu, H., Li, Y., Lu, F., Robinson, B. E., Ouyang, Z., Hai, Y., & Daily, G. C. (2021). Time and space catch up with restoration programs that ignore ecosystem service trade-offs. *Science Advances*, *7*(14), eabf8650. https://doi.org/10.1126/sciadv.abf8650

Li, R.-Q., Dong, M., Cui, J.-Y., Zhang, L.-L., Cui, Q.-G., & He, W.-M. (2007). Quantification of the impact of land-use changes on ecosystem services: A case study in Pingbian County, China. *Encironmental Monitoring and Assessment*, *128*(1–3), 503–510. https://doi.org/10.1007/s10661-006-9344-0

Li, S., Li, X., Sun, L., Cao, G., Fischer, G., & Tramberend, S. (2018). An estimation of the extent of cropland abandonment in mountainous regions of China. *Land Degradation & Development*, *29*(5), 1327–1342. https://doi.org/10.1002/ldr.2924

Li, X., Tian, Y., Gao, T., Jin, L., Li, S., Zhao, D., Zheng, X., Yu, L., & Zhu, J. (2020). Trade-Offs Analysis of Ecosystem Services for the Grain for Green Program: Informing Reforestation Decisions in a Mountainous Headwater Region, Northeast China. *Sustainability*, *12*(11). https://doi.org/10.3390/su12114762

Li, Y., Chen, H., Li, F., Jiang, L., & Zhang, J. (2024). Water yield forecast in Shandong Province based on InVEST model. *Transactions on Social Science, Education and Humanities Research*, *9*, 94–103. https://doi.org/10.62051/s85vhy98

Li, Z., Miao, X., Wang, M., Jiang, S., & Wang, Y. (2022). The Classification and Regulation of Mountain Villages in the Context of Rural Revitalization—The Example of Zhaotong, Yunnan Province. *Sustainability*, *14*(18), Article 18. https://doi.org/10.3390/su141811381

Liao, Z., Yue, C., He, B., Zhao, K., Ciais, P., Alkama, R., Grassi, G., Sitch, S., Chen, R., Quan, X., Xu, M., & Wang, M. (2024). Growing biomass carbon stock in China driven by expansion and conservation of woody areas. *Nature Geoscience*, *17*(11), 1127–1134. https://doi.org/10.1038/s41561-024-01569-0

Lin, Q., Eladawy, A., Sha, J., Li, X., Wang, J., Kurbanov, E., & Thomas, A. (2021). Remotely Sensed Ecological Protection Redline and Security Pattern Construction: A Comparative Analysis of Pingtan (China) and Durban (South Africa). *Remote Sensing*, *13*(15). https://doi.org/10.3390/rs13152865

Lin, Q., Zhang, K., Giguet-Covex, C., Arnaud, F., McGowan, S., Gielly, L., Capo, E., Huang, S., Ficetola, G. F., Shen, J., Dearing, J. A., & Meadows, M. E. (2024). Transient social–ecological dynamics reveal signals of decoupling in a highly disturbed Anthropocene landscape. *Proceedings of the National Academy of Sciences*, *121*(17), e2321303121. https://doi.org/10.1073/pnas.2321303121

Lin, Q., Zhang, K., Shen, J., & Liu, E. (2019). Integrating long-term dynamics of ecosystem services into restoration and management of large shallow lakes. *Science of The Total Environment*, *671*, 66–75. https://doi.org/10.1016/j.scitotenv.2019.03.307

Liu, C., Yang, M., Hou, Y., & Xue, X. (2021). Ecosystem service multifunctionality assessment and coupling coordination analysis with land use and land cover change in China's coastal zones. *Science of The Total Environment*, *797*, 149033. https://doi.org/10.1016/j.scitotenv.2021.149033

Liu, H., Liu, S., Wang, F., Liu, Y., Liu, Y., Sun, J., McConkey, K. R., Tran, L.-S. P., Dong, Y., Yu, L., & Wang, Q. (2023). Identifying ecological compensation areas for ecosystem services degradation on the Qinghai-Tibet Plateau. *Journal of Cleaner Production*, *423*, 138626. https://doi.org/10.1016/j.jclepro.2023.138626

Liu, J., Fang, Y., Wang, G., Liu, B., & Wang, R. (2023). The aging of farmers and its challenges for labor-intensive agriculture in China: A perspective on farmland transfer plans for farmers' retirement. *Journal of Rural Studies*, *100*, 103013. https://doi.org/10.1016/j.jrurstud.2023.103013

Liu, M., Wei, H., Dong, X., Wang, X.-C., Zhao, B., & Zhang, Y. (2022a). Integrating Land Use, Ecosystem Service, and Human Well-Being: A Systematic Review. *Sustainability*, *14*(11), 6926. https://doi.org/10.3390/su14116926

Liu, M., Wei, H., Dong, X., Wang, X.-C., Zhao, B., & Zhang, Y. (2022b). Integrating land use, ecosystem service, and human well-being: A systematic review. *Sustainability*, *14*(11), 6926. https://doi.org/10.3390/su14116926

Liu, M., Zhou, X., Huang, G., & Li, Y. (2024). The increasing water stress projected for China could shift the agriculture and manufacturing industry geographically. *Communications Earth & Environment*, *5*(1), 1–13. https://doi.org/10.1038/s43247-024-01560-y

Liu, X., Mao, G., Ren, J., Li, R. Y. M., Guo, J., & Zhang, L. (2015). How might China achieve its 2020 emissions target? A scenario analysis of energy consumption and CO_2 emissions using the system dynamics model. *Journal of Cleaner Production*, *103*, 401–410. https://doi.org/10.1016/j.jclepro.2014.12.080

Liu, X., Wang, H., Li, S., & Wang, L. (2024). Ecological protection makes the ecological Kuznets curve turning point come earlier. *Scientific Reports*, *14*(1). https://doi.org/10.1038/s41598-024-74618-8

Liu, Y., Fang, F., & Li, Y. (2014). Key issues of land use in China and implications for policy making. *Land Use Policy*, *40*, 6–12. https://doi.org/10.1016/j.landusepol.2013.03.013

Liu, Y., Zhang, Z., & Zhou, Y. (2018). Efficiency of construction land allocation in China: An econometric analysis of panel data. *Land Use Policy*, *74*, 261–272. https://doi.org/10.1016/j.landusepol.2017.03.030

Locatelli, B., Lavorel, S., Sloan, S., Tappeiner, U., & Geneletti, D. (2017). Characteristic trajectories of ecosystem services in mountains. *Frontiers in Ecology and the Environment*, *15*(3), 150–159. https://doi.org/10.1002/fee.1470

Luo, Z., Zheng, W., Liu, J., Wang, J., & Bai, X. (2024). A Multi-Objective Scenario Study of County Land Use in Loess Hilly Areas: Taking Lintao County as an Example. *Sustainability (Switzerland)*, *16*(8). Scopus. https://doi.org/10.3390/su16083178

Luyssaert, S., Jammet, M., Stoy, P. C., Estel, S., Pongratz, J., Ceschia, E., Churkina, G., Don, A., Erb, K., & Ferlicoq, M. (2014). Land management and land-cover change have impacts of similar magnitude on surface temperature. *Nature Climate Change*, *4*(5), 389–393. https://doi.org/10.1038/nclimate2196

Lv, J., Song, C., Gao, Y., Ye, S., & Gao, P. (2025). Simulation and analysis of the long-term impacts of 1.5°C global climate pledges on China's land systems. *Science China Earth Sciences*, *68*(2), 457–472. https://doi.org/10.1007/s11430-023-1501-9

Lyu, R., Clarke, K. C., Zhang, J., Feng, J., Jia, X., & Li, J. (2021). Dynamics of spatial relationships among ecosystem services and their determinants: Implications for land use system reform in Northwestern China. *Land Use Policy*, *102*. https://doi.org/10.1016/j.landusepol.2020.105231

Ma, X.-Y., Xu, Y.-F., Sun, Q., Liu, W.-J., & Qi, W. (2024). Contributing to Carbon Neutrality Targets: A Scenario Simulation and Pattern Optimization of Land Use in Shandong Province Based on the PLUS Model. *Sustainability*, *16*(12), 5180.

Maani, K. E., & Cavana, R. Y. (2007). *Systems thinking, system dynamics: Managing change and complexity*. Pearson Prentice Hall.

Maes, J., Teller, A., Erhard, M., Liquete, C., Braat, L., Berry, P., Egoh, B., Puydarrieux, P., Fiorina, C., & Santos, F. (2013). Mapping and Assessment of Ecosystems and their Services. *An Analytical Framework for Ecosystem Assessments under Action*, *5*, 1–58.

Maleki Tirabadi, M. S., Banihabib, M. E., & Randhir, T. O. (2022). An integrated framework for simultaneously modeling primary and secondary salinity at a watershed scale. *Journal of Hydrology*, *612*, 128171. https://doi.org/10.1016/j.jhydrol.2022.128171

Marks, R. B. (2017). *China: An Environmental History* (2nd edn). Rowman and Littlefield.

Marques, A., Martins, I. S., Kastner, T., Plutzar, C., Theurl, M. C., Eisenmenger, N., Huijbregts, M. A. J., Wood, R., Stadler, K., Bruckner, M., Canelas, J., Hilbers, J. P., Tukker, A., Erb, K., & Pereira, H. M. (2019). Increasing impacts of land use on biodiversity and carbon sequestration driven by population and economic growth. *Nature Ecology & Evolution*, *3*(4), 628–637. https://doi.org/10.1038/s41559-019-0824-3

Masson-Delmotte, V., Zhai, P., Pirani, A., Connors, S. L., Péan, C., Berger, S., Caud, N., Chen, Y., Goldfarb, L., & Gomis, M. (2021). Climate change 2021: The physical science basis. *Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, *2*(1), 2391.

Mastrángelo, M. E., Pérez-Harguindeguy, N., Enrico, L., Bennett, E., Lavorel, S., Cumming, G. S., Abeygunawardane, D., Amarilla, L. D., Burkhard, B., Egoh, B. N., Frishkoff, L., Galetto, L., Huber, S., Karp, D. S., Ke, A., Kowaljow, E., Kronenburg-García, A., Locatelli, B., Martín-López, B., … Zoeller, K. (2019). Key knowledge gaps to achieve global sustainability goals. *Nature Sustainability*, *2*(12), 1115–1121. https://doi.org/10.1038/s41893-019-0412-1

MEA, M. E. A. (2005). Ecosystems and human well-being: Synthesis. *Island, Washington, DC*.

Mekuria, W., Gedle, A., Tesfaye, Y., & Phimister, E. (2023). Implications of changes in land use for ecosystem service values of two highly eroded watersheds in Lake Abaya Chamo sub-basin, Ethiopia. *Ecosystem Services*, *64*, 101564. https://doi.org/10.1016/j.ecoser.2023.101564

Mengist, W., Soromessa, T., & Legese, G. (2020). Ecosystem services research in mountainous regions: A systematic literature review on current knowledge and research gaps. *Science of The Total Environment*, *702*, 134581. https://doi.org/10.1016/j.scitotenv.2019.134581

Miao, L., Zhu, F., Sun, Z., Moore, J. C., & Cui, X. (2016). China's Land-Use Changes during the Past 300 Years: A Historical Perspective. *International Journal of Environmental Research and Public Health*, *13*(9), 847. https://doi.org/10.3390/ijerph13090847

Moriasi, D. N., Gitau, M. W., Pai, N., & Daggupati, P. (2015). Hydrologic and water quality models: Performance measures and evaluation criteria. *Transactions of the ASABE*, *58*(6), 1763–1785.

Mouttaki, I., Bagdanavičiūtė, I., Maanan, M., Erraiss, M., Rhinane, H., & Maanan, M. (2022). Classifying and Mapping Cultural Ecosystem Services Using Artificial Intelligence and Social Media Data. *Wetlands*, *42*(7), 86. https://doi.org/10.1007/s13157-022-01616-9

Naderi, M. M., Mirchi, A., Bavani, A. R. M., Goharian, E., & Madani, K. (2021). System dynamics simulation of regional water supply and demand using a food-energy-water nexus approach: Application to Qazvin Plain, Iran. *Journal of Environmental Management*, *280*, 111843. https://doi.org/10.1016/j.jenvman.2020.111843

National Geomatics Center of China. (2017). *China landform dataset (1:1,000,000)* [National topographic dataset]. National Administration of Surveying, Mapping and Geoinformation of China.

Nayak, D., Shukla, A. K., & Devi, N. R. (2024). Decadal changes in land use and land cover: Impacts and their influence on urban ecosystem services. *AQUA - Water Infrastructure, Ecosystems and Society*, *73*(1), 57–72. https://doi.org/10.2166/aqua.2024.211

Nedd, R., Light, K., Owens, M., James, N., Johnson, E., & Anandhi, A. (2021). A Synthesis of Land Use/Land Cover Studies: Definitions, Classification Systems, Meta-Studies, Challenges and Knowledge Gaps on a Global Landscape. *Land*, *10*(9), Article 9. https://doi.org/10.3390/land10090994

O'Hogain, S., McCarton, L., O'Hogain, S., & McCarton, L. (2018). Nature-based solutions. *A Technology Portfolio of Nature Based Solutions: Innovations in Water Management*, 1–9. https://doi.org/10.1007/978-3-319-73281-7_1

O'Neill, B. C., Kriegler, E., Riahi, K., Ebi, K. L., Hallegatte, S., Carter, T. R., Mathur, R., & van Vuuren, D. P. (2014). A new scenario framework for climate change research: The concept of shared socioeconomic pathways. *Climatic Change*, *122*(3), 387–400. https://doi.org/10.1007/s10584-013-0905-2

Owens, K., Carmody, E., Grafton, Q., O'Donnell, E., Wheeler, S., Godden, L., Allen, R., Lyster, R., Steduto, P., Jiang, Q., Kingsford, R., & Quiggin, J. (2022). Delivering global water security: Embedding water justice as a response to increased irrigation efficiency. *WIREs Water*, *9*(6), e1608. https://doi.org/10.1002/wat2.1608

Pan, C., Wen, J., & Ma, J. (2024). Temporal and Spatial Variation in Habitat Quality in Guangxi Based on PLUS-InVEST Model. *Land*, *13*(12), Article 12. https://doi.org/10.3390/land13122250

Pan, S., Di, C., Chandio, A. A., Sargani, G. R., & Zhang, H. (2022). Investigating the Impact of Grain Subsidy Policy on Farmers' Green Production Behavior: Recent Evidence from China. *Agriculture*, *12*(8), Article 8. https://doi.org/10.3390/agriculture12081191

Pătru-Stupariu, I., Hossu, C. A., Grădinaru, S. R., Nita, A., Stupariu, M.-S., Huzui-Stoiculescu, A., & Gavrilidis, A.-A. (2020). A Review of Changes in Mountain Land Use and Ecosystem Services: From Theory to Practice. *Land*, *9*(9), 336. https://doi.org/10.3390/land9090336

Paul, C., Kuhn, K., Steinhoff-Knopp, B., Weißhuhn, P., & Helming, K. (2021). Towards a standardization of soil-related ecosystem service assessments. *European Journal of Soil Science*, *72*(4), 1543–1558. https://doi.org/10.1111/ejss.13022

Peng, W. F., Zhou, J. M., Fan, S. Y., & Yang, C. J. (2016). Effects of the Land Use Change on Ecosystem Service Value in Chengdu, Western China from 1978 to 2010. *Journal of The Indian Society of Remote Sensing*, *44*(2), 197–206. https://doi.org/10.1007/s12524-015-0481-1

Peng, Y., Welden, N., & Renaud, F. G. (2023). A framework for integrating ecosystem services indicators into vulnerability and risk assessments of deltaic social-ecological systems. *Journal of Environmental Management*, *326*, 116682. https://doi.org/10.1016/j.jenvman.2022.116682

Pepin, N. C., Arnone, E., Gobiet, A., Haslinger, K., Kotlarski, S., Notarnicola, C., Palazzi, E., Seibert, P., Serafin, S., Schöner, W., Terzago, S., Thornton, J. M., Vuille, M., & Adler, C. (2022). Climate Changes and Their Elevational Patterns in the Mountains of the World. *Reviews of Geophysics*, *60*(1), e2020RG000730. https://doi.org/10.1029/2020RG000730

Pham, Y., Reardon-Smith, K., & Deo, R. C. (2021). Evaluating management strategies for sustainable crop production under changing climate conditions: A system dynamics approach. *Journal of Environmental Management*, *292*, 112790. https://doi.org/10.1016/j.jenvman.2021.112790

Puppim, de O., Bellezoni, R. A., Shih, W., & Bayulken, B. (2022). Innovations in Urban Green and Blue Infrastructure: Tackling local and global challenges in cities. *Journal of Cleaner Production*, *362*, 132355. https://doi.org/10.1016/j.jclepro.2022.132355

Qian, D., Cao, G., Du, Y., Li, Q., & Guo, X. (2019). Impacts of climate change and human factors on land cover change in inland mountain protected areas: A case study of the Qilian Mountain National Nature Reserve in China. *Environmental Monitoring and Assessment*, *191*(8). https://doi.org/10.1007/s10661-019-7619-5

Qiu, S., Peng, J., Zheng, H., Xu, Z., & Meersmans, J. (2022). How can massive ecological restoration programs interplay with social-ecological systems? A review of research in the South China karst region. *Science of The Total Environment*, *807*, 150723. https://doi.org/10.1016/j.scitotenv.2021.150723

Rachmawati, T. S. N., & Kim, S. (2023). A risk management model of apartment development projects using system dynamics. *Journal of Asian Architecture and Building Engineering*, *22*(3), 1492–1506. https://doi.org/10.1080/13467581.2022.2086558

Radwan, T. M., Blackburn, G. A., Whyatt, J. D., & Atkinson, P. M. (2021). Global land cover trajectories and transitions. *Scientific Reports*, *11*(1), 12814. https://doi.org/10.1038/s41598-021-92256-2

Ramos, E. P., Sridharan, V., Alfstad, T., Niet, T., Shivakumar, A., Howells, M. I., Rogner, H., & Gardumi, F. (2022). Climate, Land, Energy and Water systems interactions – From key concepts to model implementation with OSeMOSYS. *Environmental Science & Policy*, *136*, 696–716. https://doi.org/10.1016/j.envsci.2022.07.007

Ratnayake, S. S., Reid, M., Larder, N., Hunter, D., Hasan, M. K., Dharmasena, P. B., Kogo, B., Senavirathna, M., & Kariyawasam, C. S. (2024). Climate and Land Use Change Pressures on Food Production in Social-Ecological Systems: Perceptions from Farmers in Village Tank Cascade Systems of Sri Lanka. *Sustainability*, *16*(19), Article 19. https://doi.org/10.3390/su16198603

Ren, Q., Liu, D., & Liu, Y. (2023). Spatio-temporal variation of ecosystem services and the response to urbanization: Evidence based on Shandong province of China. *Ecological Indicators*, *151*, 110333. https://doi.org/10.1016/j.ecolind.2023.110333

Renard, K. G., Foster, G. R., Weesies, G. A., & Porter, J. P. (1991). RUSLE: Revised universal soil loss equation. *Journal of Soil and Water Conservation*, *46*(1), 30–33.

Riano Sanchez, J. A., Vuichard, N., & Peylin, P. (2024). Projected changes in land carbon store over the 21st century: What contributions from land use change and atmospheric nitrogen deposition? *Earth System Dynamics*, *15*(5), 1227–1253. https://doi.org/10.5194/esd-15-1227-2024

Ristvey, A. G., Belayneh, B. E., & Lea-Cox, J. D. (2019). A Comparison of Irrigation-Water Containment Methods and Management Strategies Between Two Ornamental Production Systems to Minimize Water Security Threats. *Water*, *11*(12), Article 12. https://doi.org/10.3390/w11122558

Rogora, M., Frate, L., Carranza, M. L., Freppaz, M., Stanisci, A., Bertani, I., Bottarin, R., Brambilla, A., Canullo, R., & Carbognani, M. (2018). Assessment of climate change effects on mountain ecosystems through a cross-site analysis in the Alps and Apennines. *Science of the Total Environment*, *624*, 1429–1442. https://doi.org/10.1016/j.scitotenv.2017.12.155

Rounsevell, M. D., Pedroli, B., Erb, K.-H., Gramberger, M., Busck, A. G., Haberl, H., Kristensen, S., Kuemmerle, T., Lavorel, S., & Lindner, M. (2012). Challenges for land system science. *Land Use Policy*, *29*(4), 899–910. https://doi.org/10.1016/j.landusepol.2012.01.007

Roy, D., Gillespie, S. A., & Hossain, M. S. (2024). Social-ecological systems modeling for drought-food security nexus. *Sustainable Development*, *n/a*(n/a). https://doi.org/10.1002/sd.3178

Roy, P. S., Ramachandran, R. M., Paul, O., Thakur, P. K., Ravan, S., Behera, M. D., Sarangi, C., & Kanawade, V. P. (2022). Anthropogenic Land Use and Land Cover Changes—A Review on Its Environmental Consequences and Climate Change. *Journal of the Indian Society of Remote Sensing*, *50*(8), 1615–1640. https://doi.org/10.1007/s12524-022-01569-w

Roy, S. K., Alam, Md. T., Mojumder, P., Mondal, I., Kafy, A.-A., Dutta, M., Ferdous, M. N., Al Mamun, Md. A., & Mahtab, S. B. (2024). Dynamic assessment and prediction of land use alterations influence on ecosystem service value: A pathway to environmental sustainability. *Environmental and Sustainability Indicators*, *21*, 100319. https://doi.org/10.1016/j.indic.2023.100319

Salimi, S., Almuktar, S. A. A. A. N., & Scholz, M. (2021). Impact of climate change on wetland ecosystems: A critical review of experimental wetlands. *Journal of Environmental Management*, *286*, 112160. https://doi.org/10.1016/j.jenvman.2021.112160

Sardanyés, J., Ivančić, F., & Vidiella, B. (2024). Identifying regime shifts, transients and late warning signals for proactive ecosystem management. *Biological Conservation*, *290*, 110433. https://doi.org/10.1016/j.biocon.2023.110433

Scheffer, M., Barrett, S., Carpenter, S. R., Folke, C., Green, A. J., Holmgren, M., Hughes, T. P., Kosten, S., Van de Leemput, I. A., & Nepstad, D. C. (2015). Creating a safe operating space for iconic ecosystems. *Science*, *347*(6228), 1317–1319. https://doi.org/10.1126/science.aaa3769

Schirpke, U., Leitinger, G., Tasser, E., Rüdisser, J., Fontana, V., & Tappeiner, U. (2020). Functional spatial units are fundamental for modelling ecosystem services in mountain regions. *Applied Geography*, *118*, 102200. https://doi.org/10.1016/j.apgeog.2020.102200

Schirpke, U., Tappeiner, U., & Tasser, E. (2019). A transnational perspective of global and regional ecosystem service flows from and to mountain regions. *Scientific Reports*, *9*(1), 1–11. https://doi.org/10.1038/s41598-019-43229-z

Schirpke, U., Tscholl, S., & Tasser, E. (2020). Spatio-temporal changes in ecosystem service values: Effects of land-use changes from past to future (1860–2100). *Journal of Environmental Management*, *272*, 111068. https://doi.org/10.1016/j.jenvman.2020.111068

Schwaninger, M., & Grösser, S. (2020). System dynamics modeling: Validation for quality assurance. *System Dynamics: Theory and Applications*, 119–138.

Senge, P. M., & Forrester, J. W. (1980). Tests for building confidence in system dynamics models. *System Dynamics, TIMS Studies in Management Sciences*, *14*(14), 209–228.

Shaikh Shamim Hasan, Lin Zhen, Md. Giashuddin Miah, Tofayel Ahamed, & Abdus Samie. (2020). Impact of land use change on ecosystem services: A review. *Environmental Development*. https://doi.org/10.1016/j.envdev.2020.100527

Shandong Statistical Yearbook. (2022). [Data set]. http://tjj.shandong.gov.cn/col/col6279/index.html

Shao, Y., Yuan, X., Ma, C., Ma, R., & Ren, Z. (2020). Quantifying the Spatial Association between Land Use Change and Ecosystem Services Value: A Case Study in Xi'an, China. *Sustainability*, *12*(11), Article 11. https://doi.org/10.3390/su12114449

Shi, M., Wu, H., Fan, X., Jia, H., Dong, T., He, P., Baqa, M. F., & Jiang, P. (2021). Trade-Offs and Synergies of Multiple Ecosystem Services for Different Land Use Scenarios in the Yili River Valley, China. *Sustainability*, *13*(3). https://doi.org/10.3390/su13031577

Shojaie, A., & Fox, E. B. (2022). Granger Causality: A Review and Recent Advances. *Annual Review of Statistics and Its Application*, *9*(1), 289–319. https://doi.org/10.1146/annurev-statistics-040120-010930

Si, C., Li, Y., & Jiang, W. (2023). Effect of Insurance Subsidies on Agricultural Land-Use. *International Journal of Environmental Research and Public Health*, *20*(2), Article 2. https://doi.org/10.3390/ijerph20021493

Song, P., Mao, X., Li, Z., & Tan, Z. (2023). Study on the optimal policy options for improving energy efficiency and Co-controlling carbon emission and local air pollutants in China. *Renewable and Sustainable Energy Reviews*, *175*, 113167. https://doi.org/10.1016/j.rser.2023.113167

Song, W., & Deng, X. (2017a). Land-use/land-cover change and ecosystem service provision in China. *Science of The Total Environment*, *576*, 705–719. https://doi.org/10.1016/j.scitotenv.2016.07.078

Song, W., & Deng, X. (2017b). Land-use/land-cover change and ecosystem service provision in China. *Science of The Total Environment*, *576*, 705–719. https://doi.org/10.1016/j.scitotenv.2016.07.078

Song, W., Deng, X., Liu, B., Li, Z., & Jin, G. (2015). Impacts of grain-for-green and grain-for-blue policies on valued ecosystem services in Shandong Province, China. *Advances in Meteorology*, *2015*. https://doi.org/10.1155/2015/213534

Song, Y., Xue, D., Wen, Q., Ye, H., & Ma, B. (2024). Renewables' impacts on ecosystems in China. *Science*, *383*(6689), 1302–1303. https://doi.org/10.1126/science.ado6369

Spake, R., Lasseur, R., Crouzat, E., Bullock, J. M., Lavorel, S., Parks, K. E., Schaafsma, M., Bennett, E. M., Maes, J., Mulligan, M., Mouchet, M., Peterson, G. D., Schulp, C. J. E., Thuiller, W., Turner, M. G., Verburg, P. H., & Eigenbrod, F. (2017). Unpacking ecosystem service bundles: Towards predictive mapping of synergies and trade-offs between ecosystem services. *Global Environmental Change*, *47*, 37–50. https://doi.org/10.1016/j.gloenvcha.2017.08.004

Steffen, W., Rockström, J., Richardson, K., Lenton, T. M., Folke, C., Liverman, D., Summerhayes, C. P., Barnosky, A. D., Cornell, S. E., Crucifix, M., Donges, J. F., Fetzer, I., Lade, S. J., Scheffer, M., Winkelmann, R., & Schellnhuber, H. J. (2018). Trajectories of the Earth System in the Anthropocene. *Proceedings of the National Academy of Sciences*, *115*(33), 8252–8259. https://doi.org/10.1073/pnas.1810141115

Stehfest, E., van Zeist, W.-J., Valin, H., Havlik, P., Popp, A., Kyle, P., Tabeau, A., Mason-D'Croz, D., Hasegawa, T., Bodirsky, B. L., Calvin, K., Doelman, J. C., Fujimori, S., Humpenöder, F., Lotze-Campen, H., van Meijl, H., & Wiebe, K. (2019). Key determinants of global land-use projections. *Nature Communications*, *10*(1), 2166. https://doi.org/10.1038/s41467-019-09945-w

Sterman, J. (2000). *Instructor's manual to accompany business dyanmics: Systems thinking and modeling for a complex world*. McGraw-Hill.

Sterman, J. (2002). *System Dynamics: Systems thinking and modeling for a complex world*.

Stern, D. I., Common, M. S., & Barbier, E. B. (1996). Economic growth and environmental degradation: The environmental Kuznets curve and sustainable development. *World Development*, *24*(7), 1151–1160. https://doi.org/10.1016/0305-750X(96)00032-0

Stringer, L. C., Quinn, C. H., Le, H. T. V., Msuya, F., Pezzuti, J., Dallimer, M., Afionis, S., Berman, R., Orchard, S. E., & Rijal, M. L. (2018). A New Framework to Enable Equitable Outcomes: Resilience and Nexus Approaches Combined. *Earth's Future*, *6*(6), 902–918. https://doi.org/10.1029/2017EF000694

Stritih, A., Bebi, P., & Grêt-Regamey, A. (2019). Quantifying uncertainties in earth observation-based ecosystem service assessments. *Environmental Modelling & Software*, *111*, 300–310. https://doi.org/10.1016/j.envsoft.2018.09.005

Su, S., Xiao, R., Jiang, Z., & Zhang, Y. (2012). Characterizing landscape pattern and ecosystem service value changes for urbanization impacts at an eco-regional scale. *Applied Geography*, *34*, 295–305. https://doi.org/10.1016/j.apgeog.2011.12.001

Sun, J., Ni, C., & Wang, M. (2023). Analysis of Water Conservation Trends and Drivers in an Alpine Region: A Case Study of the Qilian Mountains. *Remote Sensing*, *15*(18). https://doi.org/10.3390/rs15184611

Sun, R., Jin, X., Han, B., Liang, X., Zhang, X., & Zhou, Y. (2022). Does scale matter? Analysis and measurement of ecosystem service supply and demand status based on ecological unit. *Environmental Impact Assessment Review*, *95*, 106785. https://doi.org/10.1016/j.eiar.2022.106785

TEEB, R. O. (2010). *Mainstreaming the Economics of Nature*.

Termansen, M., Chapman, D. S., Quinn, C. H., Fraser, E. D. G., Jin, N., Beharry-Borg, N., & Hubacek, K. (2019). Chapter Four - Modelling land use dynamics in socio-ecological systems: A case study in the UK uplands. In D. A. Bohan & A. J. Dumbrell (Eds), *Advances in Ecological Research* (Vol. 60, pp. 125–152). Academic Press. https://doi.org/10.1016/bs.aecr.2019.03.002

Theil, H., & Nagar, A. L. (1961). Testing the Independence of Regression Disturbances. *Journal of the American Statistical Association*. https://www.tandfonline.com/doi/abs/10.1080/01621459.1961.10482126

Thellmann, K., Cotter, M., Baumgartner, S., Treydte, A., Cadisch, G., & Asch, F. (2018). Tipping Points in the Supply of Ecosystem Services of a Mountainous Watershed in Southeast Asia. *Sustainability*, *10*(7). https://doi.org/10.3390/su10072418

Thompson, J. N., & Pagel, M. (2001). Coevolution. *Encyclopedia of Life Sciences. London: Nature Publishing Group*, 1–5.

Tian, Y. (2006). *The application of simulation to project evaluation for real estate developers in China* [Thesis, Massachusetts Institute of Technology]. https://dspace.mit.edu/handle/1721.1/37447

Tian, Y., Xu, D., Song, J., Guo, J., You, X., & Jiang, Y. (2022). Impacts of land use changes on ecosystem services at different elevations in an ecological function area, northern China. *Ecological Indicators*, *140*, 109003. https://doi.org/10.1016/j.ecolind.2022.109003

Tricco, A. C., Tetzlaff, J., & Moher, D. (2011). The art and science of knowledge synthesis. *Journal of Clinical Epidemiology*, *64*(1), 11–20. https://doi.org/10.1016/j.jclinepi.2009.11.007

Tu, C., Suweis, S., & D'Odorico, P. (2019). Impact of globalization on the resilience and sustainability of natural resources. *Nature Sustainability*, *2*(4), 283–289. https://doi.org/10.1038/s41893-019-0260-z

United Nations, N. Y. (2015). *Transforming our world: The 2030 Agenda for Sustainable Development*.

United Nations, U. N. (2024). *World Population Prospects 2024*. United Nations Department of Economic and Social Affairs, Population Division. chrome-extension://efaidnbmnnnibpcajpcglclefindmkaj/https://www.un.org/development/desa/pd/sites/www.un.org.development.desa.pd/files/undesa_pd_2024_wpp_2024_advance_unedited_0.pdf

Vander Esch, S., Sewell, A., Bakkenes, M., Berkhout, E., Doelman, J. C., Stehfest, E., Langhans, C., Fleskens, L., Bouwman, A., & Ten Brink, B. (2022). The global potential for land restoration: Scenarios for the Global Land Outlook 2. *PBL Netherlands Environmental Assessment Agency: The Hague, The Netherlands*.

Verburg, P. H., Erb, K.-H., Mertz, O., & Espindola, G. (2013). Land System Science: Between global challenges and local realities. *Current Opinion in Environmental Sustainability*, *5*(5), 433–437. https://doi.org/10.1016/j.cosust.2013.08.001

Vigl, L., Tasser, E., Schirpke, U., & Tappeiner, U. (2017). Using land use/land cover trajectories to uncover ecosystem service patterns across the Alps. *Regional Environmental Change*, *17*(8), 2237–2250. https://doi.org/10.1007/s10113-017-1132-6

Viviroli, D., Kummu, M., Meybeck, M., Kallio, M., & Wada, Y. (2020). Increasing dependence of lowland populations on mountain water resources. *Nature Sustainability*, *3*(11), 917–928. https://doi.org/10.1038/s41893-020-0559-9

Wang, B., Gao, P., Niu, X., & Sun, J. (2017). Policy-driven China's Grain to Green Program: Implications for ecosystem services. *Ecosystem Services*, *27*, 38–47. https://doi.org/10.1016/j.ecoser.2017.07.014

Wang, C., Gu, X., Zhou, X., Yang, J., Yu, T., Tao, Z., Gao, H., Liu, Q., Zhan, Y., & Wei, X. (2023). Chinese Soil Moisture Observation Network and Time Series Data Set for High Resolution Satellite Applications. *Scientific Data*, *10*(1), 424. https://doi.org/10.1038/s41597-023-02775-y

Wang, C., Wang, X., Wang, Y., Zhan, J., Chu, X., Teng, Y., Liu, W., & Wang, H. (2023). Spatio-temporal analysis of human wellbeing and its coupling relationship with ecosystem services in Shandong province, China. *Journal of Geographical Sciences*, *33*(2), 392–412. https://doi.org/10.1007/s11442-023-2088-8

Wang, J., Zhang, C., Yang, H., Mou, C., Mo, L., & Luo, P. (2018). Plant community ecological strategy assembly response to yak grazing in an alpine meadow on the eastern Tibetan Plateau. *Land Degradation & Development*, *29*(9), 2920–2931. https://doi.org/10.1002/ldr.3050

Wang, L., Zheng, H., Chen, Y., & Huang, B. (2024). Ecological redline policy strengthens sustainable development goals through the strict protection of multiple ecosystem services. *Global Ecology and Conservation*, *56*. https://doi.org/10.1016/j.gecco.2024.e03306

Wang, S., Liu, J., Wang, R., Ni, Z., Xu, S., & Sun, Y. (2012). Impact of socioeconomic development on ecosystem services and its conservation strategies: A case study of Shandong Province, China. *Environmental Monitoring and Assessnemt*, *184*(5), 3213–3229. https://doi.org/10.1007/s10661-011-2183-7

Wang, W., Wu, C., Fang, Q., & Harrison, O. I. (2023). Cultural ecosystem services evaluation in a coastal city of China using social media data. *Ocean & Coastal Management*, *242*, 106693. https://doi.org/10.1016/j.ocecoaman.2023.106693

Wang, X., Chen, B., & Dong, Q. (2023). The Limit of Urban Land Expansion Based on Population Growth and Economic Development: A Case Study of Shandong Province in China. *Sustainability*, *15*(1), Article 1. https://doi.org/10.3390/su15010073

Wang, X., Chen, W., Zhang, L., Jin, D., & Lu, C. (2010). Estimating the ecosystem service losses from proposed land reclamation projects: A case study in Xiamen. *Ecological Economics*, *69*(12), 2549–2556. https://doi.org/10.1016/j.ecolecon.2010.07.031

Wang, X., Xie, X., Wang, Z., Lin, H., Liu, Y., Xie, H., & Liu, X. (2022). Construction and Optimization of an Ecological Security Pattern Based on the MCR Model: A Case Study of the Minjiang River Basin in Eastern China. *International Journal of Environmental Research And Public Health*, *19*(14). https://doi.org/10.3390/ijerph19148370

Wang, Y., & Dai, E. (2020). Spatial-temporal changes in ecosystem services and the trade-off relationship in mountain regions: A case study of Hengduan Mountain region in Southwest China. *Journal of Cleaner Production*, *264*. https://doi.org/10.1016/j.jclepro.2020.121573

Wang, Y., Dai, E., Yin, L., & Ma, L. (2018a). Land use/land cover change and the effects on ecosystem services in the Hengduan Mountain region, China. *Ecosystem Services*, *34*, 55–67. https://doi.org/10.1016/j.ecoser.2018.09.008

Wang, Y., Dai, E., Yin, L., & Ma, L. (2018b). Land use/land cover change and the effects on ecosystem services in the Hengduan Mountain region, China. *Ecosystem Services*, *34*, 55–67. https://doi.org/10.1016/j.ecoser.2018.09.008

Wang, Z., Cao, J., Zhu, C., & Yang, H. (2020). The Impact of Land Use Change on Ecosystem Service Value in the Upstream of Xiong'an New Area. *Sustainability*, *12*(14). https://doi.org/10.3390/su12145707

Wen, A. (2023). Mountain protection and mountain development in China: Retrospect and Prospect (Chinese). *Bulletin of the Chinese Academy of Sciences*, 38(3), 376–384.

Wen, L., Li, B., Peng, Y., Zhou, Y., Weng, A., Jin, Y., Cai, G., Lin, Y., & Chen, B. (2024). Exploring the evolution of coupled natural-cultural ecosystem services and their geographically scaled driven modeling in a coastal city of Southeast China. *Journal of Environmental Management*, *361*, 121265. https://doi.org/10.1016/j.jenvman.2024.121265

Winkler, K., Fuchs, R., Rounsevell, M., & Herold, M. (2021). Global land use changes are four times greater than previously estimated. *Nature Communications*, *12*(1), 2501. https://doi.org/10.1038/s41467-021-22702-2

Wolff, S. (2023). *Analyzing spatial patterns and dynamics of landscapes and ecosystem services – Exploring fine-scale data and indicators* [Mathematisch-Naturwissenschaftliche Fakultät]. https://doi.org/10.18452/25399

World Bank. (2021). *Protecting Nature Could Avert Global Economic Losses of $2.7 Trillion Per Year*. World Bank. https://www.worldbank.org/en/news/press-release/2021/07/01/protecting-nature-could-avert-global-economic-losses-of-usd2-7-trillion-per-year

Wu, C., Chen, B., Huang, X., & Dennis Wei, Y. H. (2020). Effect of land-use change and optimization on the ecosystem service values of Jiangsu province, China. *Ecological Indicators*, *117*, 106507. https://doi.org/10.1016/j.ecolind.2020.106507

Wu, G., Li, L., Ahmad, S., Chen, X., & Pan, X. (2013). A Dynamic Model for Vulnerability Assessment of Regional Water Resources in Arid Areas: A Case Study of Bayingolin, China. *Water Resources Management*, *27*(8), 3085–3101. https://doi.org/10.1007/s11269-013-0334-z

Wu, Q., & Dai, Y. (2024). Ecological Security Patterns Research Based on Ecosystem Services and Circuit Theory in Southwest China. *SUSTAINABILITY*, *16*(7). https://doi.org/10.3390/su16072835

Wu, Q., Wang, L., Wang, T., Ruan, Z., & Du, P. (2024). Spatial–temporal evolution analysis of multi-scenario land use and carbon storage based on PLUS-InVEST model: A case study in Dalian, China. *Ecological Indicators*, *166*, 112448. https://doi.org/10.1016/j.ecolind.2024.112448

Xiao, Y., Guo, L., & Sang, W. (2020). Impact of Fast Urbanization on Ecosystem Health in Mountainous Regions of Southwest China. *International Journal of Environmental Research and Public Health*, *17*(3). https://doi.org/10.3390/ijerph17030826

Xie, G., Zhen, L., Lu, C.-X., Xiao, Y., & Chen, C. (2008). Expert knowledge based valuation method of ecosystem services in China. *Journal of Natural Resources*, *23*(5), 911–919.

Xu, D., Deng, X., Guo, S., & Liu, S. (2019a). Labor migration and farmland abandonment in rural China: Empirical results and policy implications. *Journal of Environmental Management*, *232*, 738–750. https://doi.org/10.1016/j.jenvman.2018.11.136

Xu, D., Deng, X., Guo, S., & Liu, S. (2019b). Labor migration and farmland abandonment in rural China: Empirical results and policy implications. *Journal of Environmental Management*, *232*, 738–750. https://doi.org/10.1016/j.jenvman.2018.11.136

Xu, H., Zhao, G., Fagerholm, N., Primdahl, J., & Plieninger, T. (2020). Participatory mapping of cultural ecosystem services for landscape corridor planning: A case study of the Silk Roads corridor in Zhangye, China. *Journal of Environmental Management*, *264*, 110458. https://doi.org/10.1016/j.jenvman.2020.110458

Xu, T.-T., Peng, J.-L., & Ding, F. (2013). Linkage Relationship between Port Logistics and Regional Economy based on Eviews Software. *Journal of Software*, *8*(4), 971–978. https://doi.org/10.4304/jsw.8.4.971-978

Yan, M., Duan, J., Li, Y., Yu, Y., Wang, Y., Zhang, J., & Qiu, Y. (2024). Construction of the Ecological Security Pattern in Xishuangbanna Tropical Rainforest Based on Circuit Theory. *Sustainability (Switzerland)*, *16*(8). Scopus. https://doi.org/10.3390/su16083290

Yang, J., Xing, Z., & Cheng, C. (2022). How Urban Fringe Expansion Affects Green Habitat Diversity? Analysis from Urban and Local Scale in Hilly City. *Journal of Environmental and Public Health*, *2022*. https://doi.org/10.1155/2022/8566686

Yang, L., & Cao, K. (2022). Cultural Ecosystem Services Research Progress and Future Prospects: A Review. *Sustainability*, *14*(19), Article 19. https://doi.org/10.3390/su141911845

Yang, Y. (2021). Evolution of habitat quality and association with land-use changes in mountainous areas: A case study of the Taihang Mountains in Hebei Province, China. *Ecological Indicators*, *129*. https://doi.org/10.1016/j.ecolind.2021.107967

Yi, Y., Shi, M., Liu, C., Wang, B., Kang, H., & Hu, X. (2018). Changes of Ecosystem Services and Landscape Patterns in Mountainous Areas: A Case Study in the Mentougou District in Beijing. *Sustainability*, *10*(10). https://doi.org/10.3390/su10103689

Yim, J., Kwon, B.-O., Nam, J., Hwang, J. H., Choi, K., & Khim, J. S. (2018). Analysis of forty years long changes in coastal land use and land cover of the Yellow

Sea: The gains or losses in ecosystem services. *Environmental Pollution*, *241*, 74–84. https://doi.org/10.1016/j.envpol.2018.05.058

Yu, D., & Han, S. (2016). Ecosystem service status and changes of degraded natural reserves—A study from the Changbai Mountain Natural Reserve, China. *Ecosystem Services*, *20*, 56–65. https://doi.org/10.1016/j.ecoser.2016.06.009

Yu, S., Cui, B., Xie, C., Ma, X., Man, Y., Yan, J., & Fu, J. (2021). A quantitative approach for offsetting the coastal reclamation impacts on multiple ecosystem services in the Yellow River Delta. *Ecosystem Services*, *52*, 101382. https://doi.org/10.1016/j.ecoser.2021.101382

Yu, S., Yan, Q., Deng, W., Xing, Y., & Kang, Y. (2021). A“hematopietic ecological compensation”mode appliable to the Hebeisections of the Taihang Mountain area，China (Chinese). *Mountain Research*, *39(6)*, 879－890. https://doi.org/10.16089/j．cnki．1008－2786．000646

Yuan, S., Mei, Z., Zhu, C., Cao, R., Li, S., Yang, L., Su, Y., & Li, W. (2024). Investigating the spatio-temporal interactive relationship between land use structure and ecosystem services in urbanizing China. *Ecological Indicators*, *158*, 111315. https://doi.org/10.1016/j.ecolind.2023.111315

Zhang, H., Deng, W., Zhang, S., Peng, L., & Liu, Y. (2022). Impacts of urbanization on ecosystem services in the Chengdu-Chongqing Urban Agglomeration: Changes and trade-offs. *Ecological Indicators*, *139*, 108920. https://doi.org/10.1016/j.ecolind.2022.108920

Zhang, H., Yang, Q., Zhang, Z., Lu, D., & Zhang, H. (2021). Spatiotemporal Changes of Ecosystem Service Value Determined by National Land Space Pattern Change: A Case Study of Fengdu County in The Three Gorges Reservoir Area, China. *International Journal of Environmental Research and Public Health*, *18*(9). https://doi.org/10.3390/ijerph18095007

Zhang, J., Zhao, X.-Z., Zhou, R., Tian, T., Cui, J.-Y., Zhao, L., Wang, G.-R., & Xiong, Y.-C. (2021). Labor force transfer, vegetation restoration and ecosystem service in the Qilian Mountains. *Journal Of Environmental Management*, *288*. https://doi.org/10.1016/j.jenvman.2021.112387

Zhang Juan, Chen Fan, Jiao Hongmei, Liu Chengjing, Zhao Dongmei, Liu, Z., Xu, Q., & Qiu, Y. (2020). Impacts of land use change on ecosystem services and human wellbeing in villages with different tourism patterns in Hani Terraced Fields (Chinese article). *Journal of Ecology (Chinese)*, *40*(15), 5179–5189.

Zhang, K., Dearing, J. A., Dawson, T. P., Dong, X., Yang, X., & Zhang, W. (2015). Poverty alleviation strategies in eastern China lead to critical ecological dynamics. *Science of The Total Environment*, *506–507*, 164–181. https://doi.org/10.1016/j.scitotenv.2014.10.096

Zhang, P., Liu, L., Yang, L., Zhao, J., Li, Y., Qi, Y., Ma, X., & Cao, L. (2023). Exploring the response of ecosystem service value to land use changes under multiple scenarios coupling a mixed-cell cellular automata model and system dynamics model in Xi'an, China. *Ecological Indicators*, *147*, 110009. https://doi.org/10.1016/j.ecolind.2023.110009

Zhang, Q., & Li, J. (2023). Building carbon peak scenario prediction in China using system dynamics model. *Environmental Science and Pollution Research*, *30*(42), 96019–96039. https://doi.org/10.1007/s11356-023-29168-3

Zhang, Q., Song, C., & Chen, X. (2018). Effects of China's payment for ecosystem services programs on cropland abandonment: A case study in Tiantangzhai Township, Anhui, China. *Land Use Policy*, *73*, 239–248. https://doi.org/10.1016/j.landusepol.2018.01.001

Zhang, S., Chen, W., Wang, Y., Li, Q., Shi, H., Li, M., Sun, Z., Zhu, B., & Seyoum, G. (2024). Human interventions have enhanced the net ecosystem productivity of farmland in China. *Nature Communications*, *15*(1), 10523. https://doi.org/10.1038/s41467-024-54907-6

Zhang, X., Liu, Y., Yin, J., Shi, P., Feng, H., & Shi, J. (2025). Multi-scenario simulation of land use change and its impact on ecosystem services in the northeastern edge of the Qinghai-Xizang Plateau, China. *Journal of Arid Land*, *17*(2), 145–166. https://doi.org/10.1007/s40333-025-0091-x

Zhang, X., Xu, L., & Li, C. (2022). Sustainability of Water Resources in Shandong Province Based on a System Dynamics Model of Water–Economy–Society for the Lower Yellow River. *Sustainability*, *14*(6), Article 6. https://doi.org/10.3390/su14063412

Zhao, L., Yang, C., Zhao, Y., Wang, Q., & Zhang, Q. (2023). Spatial correlations of land use carbon emissions in Shandong peninsula urban agglomeration: A perspective from city level using remote sensing data. *Remote Sensing*, *15*(6), 1488.

Zhao, Y., Wang, M., Lan, T., Xu, Z., Wu, J., Liu, Q., & Peng, J. (2023a). Distinguishing the effects of land use policies on ecosystem services and their trade-offs based on multi-scenario simulations. *Applied Geography*, *151*, 102864. https://doi.org/10.1016/j.apgeog.2022.102864

Zhao, Y., Wang, M., Lan, T., Xu, Z., Wu, J., Liu, Q., & Peng, J. (2023b). Distinguishing the effects of land use policies on ecosystem services and their trade-offs based on multi-scenario simulations. *Applied Geography*, *151*, 102864. https://doi.org/10.1016/j.apgeog.2022.102864

Zheng, H., & Li, H. (2022). Spatial–temporal evolution characteristics of land use and habitat quality in Shandong Province, China. *Scientific Reports*, *12*(1), 15422. https://doi.org/10.1038/s41598-022-19493-x

Zheng, H., & Zheng, H. (2023a). Assessment and prediction of carbon storage based on land use/land cover dynamics in the coastal area of Shandong Province. *Ecological Indicators*, *153*, 110474.

Zheng, H., & Zheng, H. (2023b). Assessment and prediction of carbon storage based on land use/land cover dynamics in the coastal area of Shandong Province. *Ecological Indicators*, *153*, 110474. https://doi.org/10.1016/j.ecolind.2023.110474

Zheng, J., Mi, Z., Coffman, D., Milcheva, S., Shan, Y., Guan, D., & Wang, S. (2019). Regional development and carbon emissions in China. *Energy Economics*, *81*, 25–36. https://doi.org/10.1016/j.eneco.2019.03.003

Zhu, B., Yang, Y., Meng, Y., & Chen, J. (2024). Assessment and multi-scenario simulation of ecosystem service values in Southwest China's mountainous and hilly region. *Open Agriculture*, *9*(1). https://doi.org/10.1515/opag-2022-0365

Zhu, L., Xing, H., & Hou, D. (2022). Analysis of carbon emissions from land cover change during 2000 to 2020 in Shandong Province, China. *Scientific Reports*, *12*(1), 8021.