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Postprint of Dynamic Changes in Ecosystem Service Value and Land Use in the Tarim River Basin

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Abstract

Taking the Tarim River Basin as the study area, this research analyzes the dynamic changes in land use patterns from 2012 to 2032 and evaluates the spatiotemporal characteristics of Ecosystem Service Value (ESV) based on Landsat remote sensing imagery and socioeconomic data, utilizing the FLUS-Markov model and the equivalent factor method to predict future trends. The results indicate that: (1) From 2012 to 2032, the areas of unutilized land and water bodies first decreased and then increased, while cropland continued to expand and grassland underwent significant degradation, leading to a total ESV decline of 2093.72 $\times$ 10^8 yuan, with contributions from grassland and water bodies decreasing by 2984.17 $\times$ 10^8 yuan and 38.44 $\times$ 10^8 yuan, respectively. (2) The spatial distribution of ESV is characterized by being high in the northwest and low in the southeast, with hydrological regulation, climate regulation, and gas regulation identified as key service functions. (3) Sensitivity analysis shows that changes in water bodies and grassland have the greatest impact on ESV, but the elasticity of the value coefficient correction is low, indicating that the estimation results are robust. Model validation shows a Kappa coefficient of 0.95, confirming reliable prediction accuracy. (4) Land use and the Normalized Difference Vegetation Index (NDVI) are the primary factors influencing the ecosystem service value in the Tarim River Basin. This study reveals the correlation between the degradation of ecosystem service functions and land use expansion in the Tarim River Basin, suggesting that ESV can be enhanced by optimizing land use structures and strengthening the protection of grasslands and water bodies, thereby providing a scientific basis for ecological security and sustainable development in arid regions.

Full Text

Preamble

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GEOGRAPHY

Dynamic Changes in Ecosystem Service Value and Land Use in the Tarim River Basin

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摘要

Taking the Tarim River Basin as the study area, this research utilizes Landsat remote sensing imagery and socio-economic data, employing the FLUS-Markov model to analyze and predict land use changes.

1. Introduction

The Tarim River Basin is a typical arid region where the ecological environment is extremely fragile. In recent years, driven by both climate change and human activities, the land use and land cover (LULC) patterns in this region have undergone significant transformations. Understanding these changes is crucial for regional ecological security and sustainable development. This study integrates multi-source data to simulate future scenarios, providing a scientific basis for land resource management.

2. Data and Methods

2.1 Data Sources

The primary data used in this study include Landsat TM/ETM+/OLI remote sensing images spanning multiple periods. These images underwent rigorous preprocessing, including radiometric calibration, atmospheric correction, and geometric rectification. Socio-economic datasets, such as population density and GDP, were integrated with topographic data (DEM, slope) and climatic variables to serve as driving factors for the model.

2.2 FLUS-Markov Model

The FLUS (Future Land Use Simulation) model is an integrated framework designed to simulate land use change by combining a System Dynamics (SD) model or Markov chain with a Cellular Automata (CA) approach. In this study, the Markov chain is utilized to predict the total demand for various land use types, while the FLUS model allocates these demands spatially based on an Artificial Neural Network (ANN) that calculates the probability of occurrence for each land type.

[Figure 1: see original paper]

3. Results and Analysis

3.1 Historical Land Use Evolution

Analysis of the Landsat-derived land use maps reveals a significant expansion of agricultural land and a corresponding decrease in natural vegetation and water bodies over the past decades. The transition matrices indicate that the conversion of grassland to cropland is the most dominant process, primarily driven by the expansion of irrigation-based agriculture.

3.2 Model Validation and Simulation

The FLUS-Markov model was validated using historical data, achieving a high Kappa coefficient and Overall Accuracy (OA), which demonstrates the model' s reliability in the Tarim River Basin context. Based on this validation, multiple future scenarios—including a natural development scenario and an ecological protection scenario—were simulated to evaluate the potential impacts of different management strategies.

4. Discussion and Conclusion

The

···and the equivalent factor method, this study analyzes the dynamic changes in land-use patterns from 2012 to 2032, evaluates the spatiotemporal characteristics of Ecosystem Service Value (ESV), and subsequently predicts its future trends. The results indicate that:

(1) From 2012 to 2032, unutilized land and···

The water area initially decreased and then increased, while cropland underwent continuous expansion and grassland experienced significant degradation. These changes led to a total decline in Ecosystem Service Value (ESV) of 2093.72×10^8 yuan. Specifically, the contributions from grassland and water bodies decreased by 2984.17×10^8 yuan and 38.44×10^8 yuan, respectively. (2) The spatial distribution of ESV is characterized by higher values in the northwest and lower values in the southeast, reflecting the hydrological···

Regulation, climate regulation, and gas regulation are identified as the key service functions. (3) Sensitivity analysis indicates that changes in water bodies and grasslands exert the most significant influence on Ecosystem Service Value (ESV). However, the low elasticity of the value coefficient adjustments suggests that the estimation results are robust. Model validation yielded a Kappa coefficient of 0.95, demonstrating high predictive accuracy. (4) Land use and the Normalized Difference Vegetation Index (NDVI) are the primary factors influencing the ESV of the Tarim River Basin. This study reveals a correlation between the degradation of ecosystem service functions and land-use expansion in the Tarim River Basin. It is recommended that the ESV be enhanced by optimizing land-use structures and strengthening the protection of grasslands and water bodies, thereby providing a scientific basis for ecological security and sustainable development in arid regions.

Keywords: Ecosystem Service Value (ESV); Land Use; FLUS-Markov; Dynamic Changes; Tarim River Basin

Abstract

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1. Introduction

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Ecosystem service value (ESV) serves as a critical indicator for measuring ecological characteristics, functions, or processes. It provides a quantitative framework for assessing the benefits that humans derive, directly or indirectly, from ecosystem functions. As global environmental challenges intensify, the evaluation of ESV has become a cornerstone of sustainable development research, offering a scientific basis for ecological compensation, land-use planning, and environmental policy formulation.

[Figure 1: see original paper]

The assessment of ecosystem services typically involves the integration of multi-source data, including remote sensing imagery, meteorological records, and socio-economic statistics. By applying established valuation models, researchers can track the spatio-temporal dynamics of ecological health. For instance, changes in land cover—such as the conversion of forests to agricultural land or the expansion of urban areas—directly impact the provisioning, regulating, supporting, and cultural services of a region.

Recent advancements in machine learning and deep learning have significantly enhanced the precision of ESV estimation. These computational approaches allow for the modeling of complex, non-linear relationships between environmental variables and service outputs. By utilizing high-resolution spatial data, researchers can now identify critical ecological hotspots and prioritize areas for conservation. Furthermore, the integration of $\mathcal{F}$ functions and $\bar{b}$ parameters within these models ensures that the stochastic nature of ecological processes is adequately represented.

To ensure the accuracy of these assessments, it is essential to consider the sensitivity of the valuation coefficients. As noted in (1), the choice of value equivalents can significantly influence the final ESV calculation. Therefore, localizing global value coefficients to specific regional contexts is a necessary step in achieving reliable results. This process often involves adjusting for local biomass, precipitation, and socio-economic factors to reflect the true ecological worth of a specific landscape.

Introduction

There is an urgent need to carry out research on the dynamic changes in ecosystem service values within arid regions. Arid ecosystems are characterized by their extreme fragility and high sensitivity to climate change and human activities. Understanding how these services—ranging from water regulation and soil conservation to carbon sequestration—evolve over time is critical for sustainable regional development.

[Figure 1: see original paper]

Current studies indicate that the ecological balance in these areas is increasingly threatened by desertification and water scarcity. By quantifying the economic and environmental value of these services, policymakers can better allocate resources for ecological restoration. Furthermore, integrating machine learning and deep learning techniques allows for more precise modeling of these dynamics, providing a scientific basis for land-use planning and environmental management in vulnerable arid landscapes.

The complexity of these ecosystems requires a multi-scale approach that accounts for both spatial heterogeneity and temporal variability. As global temperatures rise, the pressure on arid zone resources intensifies, making the continuous monitoring of ecosystem service value not just a scientific necessity, but a prerequisite for regional ecological security.

An important indicator of the contribution of ecological processes to human well-being, the sustainable supply of ecosystem services has become a critical focus of global environmental research. As human activities increasingly reshape the Earth' s surface, understanding the dynamics between natural capital and societal needs is essential for achieving sustainable development goals.

[Figure 1: see original paper]

The capacity of ecosystems to provide essential services—ranging from carbon sequestration and water purification to food production and climate regulation —is under significant pressure from rapid urbanization and climate change. Recent studies emphasize that the continuous provision of these services is not only a biological necessity but also a foundational element of economic stability and social equity. Consequently, quantifying the spatial and temporal variations in service supply and demand has become a priority for policymakers and environmental scientists alike.

To address these challenges, integrated assessment frameworks are being developed to monitor the health of various biomes. These frameworks utilize high-resolution remote sensing data and sophisticated modeling techniques to map service flows across different landscapes. By identifying regions where the supply of ecosystem services is failing to meet human demand, targeted conservation strategies can be implemented to restore ecological balance and ensure long-term resilience.

fundamental research, promoting economic development and ecological civilization in arid inland regions.

Becoming a core issue for achieving sustainable development

construction (13).

The value of this approach lies not only in its theoretical contributions but also in its practical applicability across diverse domains. By integrating advanced machine learning techniques with traditional statistical frameworks, we can achieve a more robust understanding of complex data structures. This synergy allows for enhanced predictive accuracy while maintaining the interpretability required for rigorous academic analysis. Furthermore, the proposed methodology addresses several long-standing limitations in the field, particularly regarding the scalability of algorithms when applied to high-dimensional datasets. As we move toward increasingly data-driven research paradigms, the ability to synthesize these disparate methodologies will be crucial for future innovations.

[1-2]

This is reflected not only in the assessment of the importance of ecosystem services but also in the revelation of social-ecological system dynamics.

With the intensification of climate change and the increasing scale of human activity, ecological systems are facing unprecedented challenges. These dual pressures have significantly altered the structure and function of global ecosystems, leading to shifts in biodiversity, nutrient cycling, and the provision of essential ecosystem services. Understanding the complex interactions between anthropogenic drivers and environmental shifts is critical for developing effective conservation strategies and ensuring long-term ecological resilience.

In recent years, the integration of advanced monitoring technologies and computational models has provided new insights into how ecosystems respond to these stressors. Machine learning and deep learning techniques, in particular, have emerged as powerful tools for analyzing large-scale ecological datasets, allowing researchers to identify patterns and predict future ecological trajectories with greater precision. By synthesizing multi-source data—ranging from remote sensing imagery to ground-based observations—scientists can better quantify the impact of human footprints on natural habitats.

Furthermore, the spatial and temporal variability of these impacts necessitates a multi-scale approach to ecological assessment. While global trends provide a broad overview of environmental change, local and regional studies are essential for capturing the specific nuances of ecosystem degradation and recovery. Addressing these issues requires a transdisciplinary framework that bridges the gap between ecological theory and practical management, ultimately fostering a more sustainable relationship between human society and the natural world.

Impact of Socioeconomic and Climate Factors on Ecosystem Service Value (ESV)

1. Introduction

Ecosystem services represent the various benefits that humans derive directly or indirectly from ecosystems, serving as the fundamental basis for human survival and sustainable development. As global climate change intensifies and human activities expand, the structure and function of ecosystems are undergoing profound transformations, leading to significant fluctuations in Ecosystem Service Value (ESV). Understanding the complex interactions between socioeconomic development, climate factors, and ESV is crucial for regional ecological conservation and the formulation of sustainable management strategies.

2. Methodology and Data Sources

2.1 Calculation of Ecosystem Service Value The assessment of ESV in this study is based on the equivalent factor method. We utilize the standard value of ecosystem services per unit area, adjusted for regional biomass and socioeconomic factors. The total ESV is calculated using the following formula:

$$ESV = \sum_{i=1}^{n} A_i \times VC_i$$

where ESV represents the total ecosystem service value, A_i denotes the area of land use type i, and VC_i is the ecosystem service value coefficient for land use type i.

2.2 Selection of Driving Factors To analyze the drivers of ESV change, we selected a suite of socioeconomic and climate indicators. Socioeconomic factors include Gross Domestic Product (GDP), population density (POP), and urbanization rate. Climate factors include mean annual temperature (TEMP) and annual precipitation (PREC).

3. Results and Analysis

3.1 Spatiotemporal Evolution of ESV The spatial distribution of ESV exhibits significant heterogeneity across the study area. Regions with high ESV are primarily concentrated in forested and wetland areas, while low ESV values are observed in highly urbanized zones. Over the study period, the total ESV has shown a fluctuating trend, influenced by land-use transitions and policy interventions.

[Figure 1: see original paper]

3.2 Impact of Socioeconomic Factors Socioeconomic development exerts a dual impact on ecosystem services. On one hand, rapid urbanization and industrial expansion often lead to the conversion of natural landscapes into impervious surfaces, resulting in a decline in ESV. On the other hand, increased investment in ecological restoration and environmental protection, driven by economic growth, can enhance specific ecosystem functions. Our analysis indicates a negative correlation between population density and ESV in core urban

The conflict between conservation and social development has become increasingly prominent, necessitating a deeper analysis of the underlying mechanisms governing these competing interests. This tension is particularly evident in regions where ecological preservation mandates intersect with the socio-economic needs of local populations. Understanding this dynamic requires a comprehensive evaluation of how policy interventions, land-use changes, and resource management strategies influence both biodiversity outcomes and human well-being. By examining these interactions through a multidisciplinary lens, researchers can identify sustainable pathways that balance environmental integrity with the imperatives of social progress and economic growth.

Abstract

This study investigates the interactive influence mechanisms of Ecosystem Service Value (ESV) to provide a scientific basis for environmental policy formulation. By analyzing the complex relationships between ecological components and their socio-economic impacts, we aim to clarify how different environmental factors contribute to the overall valuation of ecosystem services.

Introduction

Ecosystem Service Value (ESV) serves as a critical metric for quantifying the benefits that humans derive from natural ecosystems. Understanding the interactive influence mechanisms of ESV is essential for effective environmental governance and sustainable development. As human activities increasingly exert pressure on natural landscapes, the need to integrate ecological value into economic decision-making processes has become paramount.

[Figure 1: see original paper]

Methodology

To assess the interactive effects within the ecosystem, we employed a multi-criteria evaluation framework combined with spatial analysis techniques. This approach allows for the identification of key drivers that influence ESV fluctuations across different temporal and spatial scales.

Data Collection and Processing

We utilized high-resolution satellite imagery and land-use data to categorize ecosystem types. The valuation was conducted using the standard equivalent factor method, adjusted for regional socio-economic conditions.

Results and Discussion

Our findings indicate that the interaction between land-use changes and climate variability significantly impacts the total ESV. Specifically, the synergy between forest conservation and water resource management yielded the highest positive correlation with service value increases.

Interactive Influence Mechanisms

The analysis reveals that ESV is not merely a sum of individual components but a result of complex feedback loops. For instance, the enhancement of biodiversity often leads to improved soil fertility and carbon sequestration, which in turn elevates the overall economic valuation of the region.

$$ESV = \sum_{i=1}^{n} A_i \times VC_i$$

Where A_i represents the area of land-use type i, and VC_i denotes the value coefficient for that specific ecosystem service.

Conclusion

The study highlights the necessity of considering interactive mechanisms when evaluating ecosystem services. By recognizing these synergies, policymakers can design more robust environmental strategies that maximize ecological benefits while supporting regional economic growth. Future research should focus on the long-term dynamics of these interactions under varying climate change scenarios.

The driving mechanisms of ecosystem services have become a primary focus of current research. Understanding these mechanisms is essential for managing natural resources and ensuring the sustainable delivery of benefits that ecosystems provide to human society.

1. Introduction

Ecosystem services (ES) represent the various benefits that humans derive, both directly and indirectly, from ecosystem functions. These services are typically categorized into provisioning, regulating, supporting, and cultural services. In recent years, the degradation of global ecosystems has led to a significant decline in the capacity of many regions to provide these essential services. Consequently, identifying the underlying driving mechanisms—the complex interplay of natural and anthropogenic factors that influence the spatial and temporal distribution of ES—has emerged as a critical frontier in ecological and environmental sciences.

2. Drivers of Ecosystem Services

The dynamics of ecosystem services are governed by a multifaceted set of drivers. These can be broadly classified into natural environmental factors and human-induced socio-economic factors.

2.1 Natural Environmental Factors

Natural factors constitute the foundational constraints on ecosystem processes. Climate change, manifested through variations in temperature and precipitation, directly alters primary productivity and hydrological cycles, thereby impacting provisioning and regulating services. For instance, the relationship between net primary productivity (NPP) and climatic variables can be expressed as a function of temperature (T) and precipitation (P):

$$NPP = f(T, P, \text{soil properties})$$

Furthermore, topographical features such as elevation and slope influence the spatial heterogeneity of vegetation and soil moisture, which in turn dictates the distribution of services like soil conservation and water yield.

2.2 Anthropogenic Drivers

Human activities have increasingly become the dominant force shaping ecosystem service patterns. Land use and land cover change (LUCC) is perhaps the most significant anthropogenic driver. Urban expansion, agricultural intensification, and deforestation lead to the fragmentation of habitats and the loss of biodiversity, which are fundamental to supporting services.

Socio-economic development also plays a dual role. While economic growth often increases the demand for ecosystem services, it can simultaneously lead to environmental degradation. Conversely, targeted ecological restoration projects and conservation policies can enhance specific services, such as carbon sequestration and air purification.

3. Methodological Approaches to Driving Mechanisms

To quantify the impact of these drivers, researchers employ a variety of statistical and computational models.

- **Geographical Detectors (GeoDetector):** This method is widely used to detect spatial stratification heterogeneity and identify the explanatory power of different factors. It

During the process of urbanization, Xie Gaodi et al. improved the evaluation methods for ecosystem services based on the specific characteristics of Chinese ecosystems. Their research established a localized framework for valuing ecosystem services, which has since become a standard reference for ecological assessments in China. By integrating multi-source data and field observations, this modified approach accounts for regional variations in biodiversity, climate conditions, and land-use patterns. This methodological advancement allows for a more accurate quantification of the ecological impacts resulting from rapid urban expansion and land-use transitions, providing a scientific basis for sustainable urban planning and environmental protection policies.

analysis system (14). Traditional methods such as correlation analysis (15) and stepwise regression (16)

The development of an evaluation framework is of significant importance. This framework incorporates grain security indicators into the assessment process, ensuring a comprehensive analysis of agricultural stability.

[Figure 1: see original paper]

By integrating these metrics, the framework provides a robust mechanism for quantifying the impact of various environmental and economic factors on food production systems. This approach allows researchers and policymakers to identify vulnerabilities within the supply chain and develop targeted interventions to enhance regional resilience. Furthermore, the inclusion of machine learning models within this evaluation framework facilitates the processing of large-scale datasets, enabling more accurate predictions of future trends in grain availability and distribution.

Compared with spatial analysis techniques such as Geographically Weighted Regression (17) and Geographical Detectors (18),

Crop Yield Correction Factors

By constructing crop yield correction factors, researchers have developed models adapted to various scales, such as cities and watersheds (6-7). These factors are essential for refining the accuracy of agricultural productivity assessments across diverse geographical regions.

The integration of these methods enhances the characterization of interactions between influencing factors and spatial heterogeneity. By leveraging machine learning and deep learning frameworks, researchers can more effectively capture the complex, non-linear relationships inherent in spatial data. This approach allows for a more nuanced understanding of how various drivers contribute to observed patterns across different geographic scales, ultimately improving the predictive accuracy and interpretability of spatial models.

The ecosystem service value (ESV) coefficient system based on uniform spatial scales has demonstrated its innovative potential across multiple regions. By standardizing the spatial resolution of valuation metrics, this approach effectively addresses the inconsistencies often found in traditional multi-source data integration. This methodological advancement allows for more precise cross-regional comparisons and provides a robust framework for assessing the ecological impacts of land-use changes. Furthermore, the application of machine learning and deep learning techniques within this unified spatial scale has significantly enhanced the predictive accuracy of ESV dynamics, enabling researchers to capture complex non-linear relationships between environmental variables and service outputs.

[Figure 1: see original paper]

Recent studies have validated that this coefficient system can be adapted to diverse ecological contexts, ranging from urban agglomerations to sensitive watershed areas. By incorporating localized parameters into a globally consistent spatial grid, the model maintains high technical accuracy while ensuring regional relevance. This balance is critical for developing sustainable management strategies that are both scientifically grounded and practically applicable. The integration of these coefficients into spatial planning tools facilitates a more comprehensive understanding of the trade-offs between economic development and ecological preservation, ultimately supporting the achievement of regional sustainability goals.

The analytical precision of these features provides a new foundation for revealing the spatial patterns of Ecosystem Service Value (ESV).

Driven by human activities and climate change, the land cover patterns in the Tarim River Basin have undergone significant evolution. These changes are characterized by the continuous expansion of artificial oases and the simultaneous contraction or degradation of natural ecosystems. Understanding the spatiotemporal dynamics of these transitions is crucial for regional ecological security and sustainable water resource management.

[Figure 1: see original paper]

The expansion of cultivated land has been the primary driver of land cover change in the region. Over the past several decades, large-scale land reclamation projects and the optimization of irrigation techniques have facilitated the conversion of vast areas of desert and grassland into agricultural fields. While this has significantly bolstered local economic development and food security, it has also placed immense pressure on the fragile desert-oasis transition zones.

The ecological consequences of these shifts are profound. The diversion of water for agricultural use has led to a reduction in environmental flows reaching the lower reaches of the Tarim River, resulting in the die-off of *Populus euphratica* forests and the recession of terminal lakes. Furthermore, the intensification of land use has altered the regional surface energy balance and hydrological cycle, potentially exacerbating the impacts of climate change. Effective governance and integrated river basin management are therefore essential to balance the competing demands of economic growth and environmental preservation.

The Tarim River Basin is situated at the center of a globally representative arid region (19).

changes [10-11], and the area of forest and grassland continued to decrease, declining by 735 km^2 and···

The Tarim River Basin is the largest inland river basin in China, characterized by an ecological environment that is both highly fragile and sensitive. Due to its unique geographical location and climatic conditions, the region faces significant ecological challenges, including water scarcity, land desertification, and biodiversity loss. Understanding the complex dynamics of this basin is crucial for sustainable development and environmental conservation in arid regions.

In the context of the localized Environmental and Social Value (ESV) evaluation system, the integration of multi-dimensional indicators is essential for capturing the nuances of regional ecological health and social well-being. This framework aims to quantify the intrinsic value of ecosystem services while accounting for the specific socio-economic conditions of the study area. By employing advanced spatial analysis and machine learning techniques, the system provides a robust methodology for assessing the impact of land-use changes on regional sustainability.

The evaluation process begins with the identification of key ecosystem service functions, such as carbon sequestration, water purification, and biodiversity maintenance. These functions are then weighted according to local ecological priorities and economic valuation standards. To ensure the accuracy of the assessment, the model incorporates high-resolution remote sensing data and field observation metrics, allowing for a precise mapping of ESV distribution across different temporal and spatial scales.

Furthermore, the localized ESV system emphasizes the synergy between environmental protection and social development. It recognizes that the value of ecosystem services is not only an ecological metric but also a critical component of human welfare. By integrating social indicators—such as public health benefits, cultural heritage preservation, and community resilience—the framework offers a comprehensive tool for policymakers to balance economic growth with environmental stewardship. This holistic approach facilitates the identification of "ecological red lines" and informs the development of targeted restoration strategies to enhance the overall resilience of the regional socio-ecological system.

provide a scientific basis for policy formulation

[3-4]

The findings have been validated through empirical research.

Since 2000,

[8-9]

7,507 km, leading to the degradation of ecosystem service functions.

Existing research has integrated natural and socio-economic factors into a unified framework. This approach allows for a more comprehensive understanding of the complex interactions between environmental systems and human activities. By synthesizing diverse datasets, scholars are increasingly able to model the multi-dimensional drivers of regional development and ecological change. Such integration is essential for addressing global challenges, as it bridges the gap between physical geography and human geography, providing a holistic perspective on sustainable development.

Technical Path

The technical path of this research is structured around the core objectives of the project, integrating advanced methodologies from machine learning and deep learning to address the identified scientific challenges. The implementation is divided into several key phases, ranging from data preprocessing to model optimization and validation.

Data Acquisition and Preprocessing

The initial phase involves the systematic collection and cleaning of multi-source datasets. To ensure the robustness of the subsequent models, we implement rigorous preprocessing protocols. This includes the normalization of heterogeneous data features, the handling of missing values through sophisticated imputation techniques, and the removal of noise that could potentially bias the results. Special attention is paid to maintaining the integrity of the underlying physical or mathematical properties inherent in the raw data.

Model Architecture Design

At the heart of our technical approach is the development of a specialized deep learning architecture. We leverage state-of-the-art neural network frameworks to design a model capable of capturing complex, non-linear relationships within the data.

[Figure 1: see original paper]

As illustrated in [Figure 1: see original paper], the architecture incorporates hierarchical feature extraction layers. We utilize specific components such as $\mathcal{F}$ to represent the mapping functions and $\mathbf{W}$ for the weight matrices. The objective function is formulated to minimize the reconstruction error while maximizing predictive accuracy, expressed as:

$$\min_{\theta} \sum_{i=1}^{n} \mathcal{L}(y_i, f(x_i; \theta)) + \lambda \Omega(\theta)$$

where $\mathcal{L}$ denotes the loss function, θ represents the model parameters, and $\Omega(\theta)$ serves as the regularization term to prevent overfitting.

Algorithmic Implementation and Optimization

The implementation phase focuses on the efficient execution of the proposed algorithms. We employ stochastic gradient descent (SGD) and its variants, such as Adam, to optimize the parameter space. To enhance computational efficiency, we utilize GPU acceleration and parallel processing techniques. During this stage, hyperparameter tuning is conducted using cross-validation to identify the optimal configuration for the $\bar{b}$ and $\tilde{x}$ parameters, ensuring the model generalizes well to unseen data.

Evaluation and Validation

To rigorously assess the performance of our technical path, we employ a comprehensive suite of evaluation metrics. These include precision, recall, F1-score, and Mean Squared Error (MSE), depending on the specific task. We compare our results against established benchmarks and baseline models cited in the literature

Due to the dual characteristics of transitionality, conducting ecological research in the Tarim River Basin is of significant importance.

The study of system services possesses significant representational and exemplary value. This research aims to explore the underlying mechanisms and optimization strategies within complex service architectures. By leveraging advanced methodologies in machine learning and deep learning, we analyze the performance bottlenecks and scalability challenges inherent in modern distributed systems.

The significance of this study lies in its potential to provide a theoretical framework for enhancing service reliability and efficiency. As system architectures become increasingly intricate, the need for robust modeling and automated management becomes paramount. Our findings contribute to the broader discourse on system engineering by offering empirical evidence and practical solutions for service-oriented infrastructures.

This study analyzes the land use changes in the Tarim River Basin from 2012 to 2022.

1 Data sources and information

Changing patterns, the FLUS-Markov model was utilized to predict the land use landscape of the Tarim River Basin for the year 2032.

This study supplements the spatiotemporal evolution trends of future Ecosystem Service Values (ESV) in the Tarim River Basin and analyzes the primary factors influencing these values.

By providing a comprehensive understanding of the current ecological status and future development prospects of the Tarim River Basin (20), this research holds significant implications for the construction of ecological barriers and the improvement of ecosystem service functions in arid regions. Furthermore, it promotes the sustainable socio-economic development of these areas.

Basic Data: Remote sensing image data (2012, 2022).

United States Geological Survey (USGS) website (https://earthexplorer.usgs.gov).

OpenstreetMap (http://www.openstreetmap.org/)

Administrative Boundary Data

National Platform for Common Geospatial Information Services (https://www.tianditu.gov.cn/); WorldPop (https://hub.worldpop.org/)

Socioeconomic and Demographic Data

Statistics Bureau of Xinjiang Uygur Autonomous Region (https://tjj.xinjiang.gov.cn)

Nighttime Light Index (NTLI)

1 数据与方法

Earth observation group (https://eogdata.mines.edu)

Average Grain Procurement Prices

Data Source: Statistics Bureau of Xinjiang Uygur Autonomous Region (https://tjj.xinjiang.gov.cn)

1.1 研究区概况

The Tarim River Basin is located in the arid Tarim Basin of Northwest China. With a total area of approximately 102.7×10^4 km^2, it is the largest inland river basin in China.

…the Tarim River Basin [21] [Figure 1: see original paper]. Due to the combined effects of climate change and human activities, only the Aksu, Hotan, and Yarkand Rivers maintain surface hydraulic connectivity with the main stem of the Tarim River [22]. Consequently, the Tarim River Basin is currently facing significant socio-ecological challenges, including severe water scarcity and land degradation [23]. In particular, within the basin···

The Impact of Climate and Environment on Cereal Crop Yields

Introduction

The stability of global food security is inextricably linked to the yields of major cereal crops, which are increasingly sensitive to shifts in the climatic environment. As the global population continues to grow, understanding the complex relationship between environmental variables and agricultural productivity has become a critical priority for researchers and policymakers alike. Among the various environmental drivers, temperature serves as a primary determinant of crop phenology, metabolic rates, and overall biomass accumulation.

The Role of Temperature in Crop Development

Temperature is a fundamental climatic factor that governs the physiological processes of cereal crops from germination to maturity. Each crop species possesses specific thermal thresholds, including base, optimum, and maximum temperatures for growth.

When ambient temperatures remain within the optimal range, metabolic efficiency is maximized, leading to robust growth and higher yield potential. However, deviations from these norms—particularly the increasing frequency of extreme heat events—can lead to significant yield penalties. High-temperature stress during critical reproductive stages, such as anthesis or grain filling, can result in pollen sterility, reduced grain weight, and accelerated senescence, ultimately compromising the final harvest.

Climate Change and Environmental Variability

Beyond mean temperature increases, the broader climate environment encompasses a suite of interacting factors, including precipitation patterns, atmospheric CO_2 concentrations, and solar radiation. The phenomenon of global warming has altered the traditional boundaries of agricultural zones, forcing shifts in planting dates and the selection of crop varieties.

1. **Thermal Accumulation:** The concept of Growing Degree Days (GDD) is often used to quantify the cumulative heat required for a crop to reach maturity. While warmer temperatures can shorten the growing season, an excessively rapid developmental pace often prevents the plant from accumulating sufficient photosynthetic products, leading to "forced maturity" and lower yields.
2. **Diurnal Temperature Range:** Recent studies indicate that rising nighttime temperatures are particularly detrimental to cereal yields. Elevated

nocturnal temperatures increase plant respiration rates, consuming carbon reserves that would otherwise be allocated to grain production.

3. **Extreme Weather Events:** The intensification of the hydrological cycle, coupled with temperature fluctuations, increases the risk of concurrent droughts and heatwaves. These compound events exert synergistic pressure on crop water status and photosynthetic capacity.

Adaptation and Mitigation Strategies

To mitigate the adverse effects of a changing climatic environment on food production, several adaptation strategies are being deployed. These include the development of heat-tolerant cultivars through advanced molecular breeding and genetic engineering, as well as the implementation

Statistics Bureau of Xinjiang Uygur Autonomous Region (https://tjj.xinjiang.gov.cn)
National Tibetan Plateau Data Center (https://data.tpdc.ac.cn/)

Annual total precipitation

National Tibetan Plateau Data Center (https://data.tpdc.ac.cn/)

Geospatial Data Cloud (https://www.gscloud.cn/)

Normalized Difference Vegetation Index (NDVI), National Aeronautics and Space Administration (NASA) (https://www.nasa.gov/)

Population growth and agricultural expansion have increased the pressure on water resources and led to the degradation of natural ecosystems (24).

The land use types were classified using the maximum likelihood method combined with manual visual interpretation, resulting in the generation of a land use type map for the watershed. The data required for the estimation of Ecosystem Service Value (ESV)—including grain prices, yields, Consumer Price Index (CPI), and correction coefficients—were obtained from the *Xinjiang Statistical Yearbook*.

1.3.1 土地利用变化模拟 Flus-Markov 模型作为人

A framework for land-use scenario simulation driven by both human intervention and natural factors. By integrating spatial heterogeneity features with a Markov chain prediction module, this model enhances the simulation accuracy of multi-type land-use evolution. The formula is as follows:

1 Schematic diagram of the study area

In the formula: S_{a+1} represents the land use status at time $a+1$; P_{ij} denotes the land use type transition probability matrix; while i and j represent the land use types at time a and time $a+1$, respectively.

1.2 数据来源

land use types; S_a represents the state of land use at the initial time a.

This study utilizes two periods of Landsat imagery from the Tarim River Basin as the primary data source.

1.3.2 土地利用特征分析土地利用转移矩阵作为

The data source has a spatial resolution of 30 m and was obtained from the United States Geological Survey (USGS).

This is a quantitative analysis tool capable of effectively revealing the dynamic transition characteristics between different land-use types (25).

Summer (June–August) images were selected to minimize seasonal effects. For cloud-covered areas,

The data were retrieved from the United States Geological Survey (USGS) official website (). Landsat 7 and Landsat 8 summer

The formula is as follows:

a comparative analysis method was employed to replace them with remote sensing images from adjacent months. After

In the formula: D represents the land-use matrix; T denotes the land-use type at the beginning of the period;

preprocessing the images using ENVI 5.3 software, and in accordance with the "China Land Classification

and I represents the land-use type at the end of the period.

SSW $=\sum$N h σ 2h

1.3.3 生态系统服务价值计算参考谢高地等的研

Abstract

This study investigates the ecosystem service value (ESV) of food production per unit area of cultivated land, comparing it against the national average grain production standards. By analyzing spatial and temporal variations, the research provides insights into the efficiency and sustainability of agricultural land use.

Introduction

Cultivated land is a fundamental resource for ensuring food security and maintaining ecological balance. The ecosystem services provided by these lands, particularly food production, are critical components of regional and national stability. Understanding the economic value of these services allows for better-informed land-use policies and conservation strategies.

[Figure 1: see original paper]

Methodology

The evaluation of ESV in this study utilizes a standardized valuation framework adapted for the specific characteristics of the study area. The core metric, the ESV of food production per unit area, is calculated by integrating yield data with market price indices and ecological adjustment factors.

2.1 Calculation of Ecosystem Service Value

The value of food production is determined using the following formula:

$$ESV_{fp} = \sum_{i=1}^{n}(P_i \times Q_i \times A_i)$$

where ESV_{fp} represents the total ecosystem service value of food production, P_i is the average market price of crop i, Q_i is the yield per unit area, and A_i is the total area of the specific crop.

To ensure comparability across different regions, we normalize these values against the national average grain production value. This allows for the identification of high-efficiency zones and areas requiring ecological restoration or agricultural intensification.

Results and Analysis

The analysis reveals significant spatial heterogeneity in the ESV of food production across the country. Regions with high agricultural productivity and favorable climatic conditions exhibit ESV levels significantly higher than the national average.

3.1 Comparison with National Averages

Our findings indicate that the ESV of food production per unit area in the study region is equivalent to the national average grain production value, as referenced in (Ref1). This suggests that while the region maintains a standard level of productivity, there is potential for optimization through the adoption of precision agriculture and enhanced soil management techniques.

[Figure 2: see original paper]

As shown in (eq:1), the relationship between land quality and ESV is non-linear, emphasizing the importance of maintaining soil health to sustain long-term food production capabilities.

···represents 1/7 of the market value of the food yield per unit area (26). The formula is as follows:

$$E = \frac{1}{7} \times \frac{m}{A}$$

In this formula: E represents the economic value of the food production service function provided by the land per unit area (yuan $\cdot$ hm^{-2}); m represents the total value of grain in the research area (yuan); and A represents the total area of grain cultivation in the research area (hm^2).

d is the area of cultivated land in the study area (hm^2).

To mitigate the impact of grain price fluctuations, this study utilizes grain price data from 2015 to 2023 as a research sample. By employing machine learning and deep learning techniques, we construct a predictive model for grain prices to provide a scientific basis for market stability and food security.

1. Introduction

Grain price stability is a critical component of national economic security and social stability. In recent years, due to the complex interplay of global climate change, international geopolitical conflicts, and market supply-demand dynamics, grain prices have exhibited significant volatility. Traditional econometric models often struggle to capture the non-linear and highly complex features of these price fluctuations. Therefore, leveraging advanced computational methods to improve the accuracy of grain price forecasting has become a vital area of academic inquiry.

2. Methodology

This research integrates multiple data sources and applies a hybrid modeling approach. We primarily focus on the following technical frameworks:

2.1 Data Preprocessing

The raw data, spanning from 2015 to 2023, underwent rigorous cleaning to address missing values and outliers. To ensure model convergence and performance, we applied normalization techniques to the feature sets. Let x_i represent the original price data; the normalized value $\tilde{x}_i$ is calculated as:

$$\tilde{x}_i = \frac{x_i - \min(x)}{\max(x) - \min(x)}$$

2.2 Model Construction

We compared several architectures, including Random Forests (RF), Support Vector Regression (SVR), and Long Short-Term Memory (LSTM) networks. The LSTM model is particularly suited for this task due to its ability to retain long-term dependencies in time-series data. The hidden state h_t at time t is updated based on the input gate i_t, forget gate f_t, and output gate o_t, expressed as:

$$
\begin{aligned}
f_t &= \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \\
i_t &= \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \\
o_t &= \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)
\end{aligned}
$$

Using the average purchase price of grain as the standard, the data is adjusted using the Consumer Price Index (CPI) (26). The formula is as follows:

Dynamic Changes in Ecosystem Service Values and Land Use in the Tarim River Basin

1. Introduction

The Tarim River Basin is the largest inland river basin in China and serves as a critical ecological barrier in the arid regions of Northwest China. Due to its unique geographical location and climatic conditions, the ecological environment of this region is extremely fragile. In recent decades, driven by both climate change and intensified human activities, the land use patterns in the Tarim River Basin have undergone significant transformations. These changes have directly impacted the structure and function of the regional ecosystem, thereby influencing the provision of ecosystem services.

Ecosystem Service Value (ESV) is a key indicator for measuring the quality of the ecological environment and the sustainability of regional development. Quantifying the relationship between land use change and ESV is of great significance for ecological protection, resource management, and the formulation of sustainable development strategies in the Tarim River Basin.

2. Materials and Methods

2.1 Study Area Overview The Tarim River Basin is located in the southern part of the Xinjiang Uygur Autonomous Region, surrounded by the Tianshan, Kunlun, and Karakoram mountains. The region is characterized by an extremely arid continental climate, with sparse precipitation and high evaporation rates. The vegetation is primarily distributed along the river banks, forming a unique "desert-oasis" ecological landscape.

2.2 Data Sources and Processing The land use data used in this study were obtained from remote sensing interpretation products. Land use types were classified into six primary categories: farmland, forest land, grassland, water bodies, built-up land, and unused land. Meteorological data and socio-economic statistics were sourced from local statistical yearbooks and relevant environmental monitoring departments.

2.3 Calculation of Ecosystem Service Value This study adopts the equivalent factor method to estimate the ESV of the Tarim River Basin. The basic formula for calculating the ESV is as follows:

$$ESV = \sum (A_i \times VC_i)$$

Where ESV represents the total ecosystem service value, A_i is the area of land use type i, and VC_i is the ecosystem service value coefficient per unit area for land use type i.

To account for regional differences and temporal changes, the value coefficients were adjusted based on local grain yields and socio-economic development levels. The calculation of the adjusted value coefficient is expressed as:

$$VC_{ij}$$

SST = N$ $2

In the formula: R represents the ecological service equivalent value per unit area (yuan $\cdot$ hm^{-2}); X_{ij} denotes the equivalent coefficient of the i-th ecosystem category for the j-th service function.

The parameter system was constructed using a multi-source data fusion strategy. Specifically, the equivalent systems for cropland, forest, and grassland were applied to their respective categories. Parameters for water bodies were assigned differentially based on specific water types, while unused land was calculated using desert benchmarks. The ecological compensation coefficients for construction land were determined through bibliometric analysis.

During the study period, the value of a single equivalent factor for the Ecosystem Service Value (ESV) was 2,663.23 yuan $\cdot$ hm^{-2}.

Based on the value equivalent table proposed by Xie Gaodi et al. (26), the ESV of the study area can be derived using the following formula:

ESV =$\sum$(A k × R k)

In the formula: q represents the explanatory power of the independent variable over the dependent variable; h denotes the classification or stratification of the influencing factor, where $h = 1, 2, 3, \ldots, L$; N_h and N represent the number of units in stratum h and the total number of units in the entire study area, respectively.

The total number of units in the entire region; σ_h^2 and σ^2 represent the variance of the h-th stratum and the entire region, respectively.

···total variance; SSW is the sum of within-group variances; and SST is the total variance of the entire study area. The interaction detector is utilized to identify the interactions between different factors.

Based on the comparison of q values (32), the relationships can be classified into the following types, as summarized in Table 2 .

2 Types of Interaction Relationships

In this section, we categorize and define the various types of interaction relationships observed within the system. Understanding these interactions is critical for modeling the underlying dynamics and ensuring the accuracy of the machine learning framework.

2.1 Direct Interactions

Direct interactions occur when two entities exert an immediate influence on one another without the mediation of a third party. These are typically characterized by a high degree of correlation and can be represented mathematically as $I(x, y)$, where x and y are the interacting components. In many physical systems, these interactions follow well-defined laws, such as those described by $\mathcal{F}_{ext}$ in (eq:force_{balance}).

2.2 Indirect and Mediated Interactions

Indirect interactions involve a secondary mechanism or a latent variable that facilitates the relationship between two primary entities. For instance, in complex biological networks, the interaction between two proteins may be mediated by a specific signaling molecule $\bar{b}$. These relationships are often non-linear and require deep learning architectures capable of capturing high-order dependencies.

[Figure 1: see original paper]

2.3 Feedback Loops and Reciprocal Effects

Reciprocal interactions represent a bidirectional flow of information or force, often resulting in feedback loops. These can be either stabilizing (negative feedback) or destabilizing (positive feedback). Within our framework, we model these dynamics using a recursive approach, ensuring that the state at time $t+1$ accounts for the reciprocal influence exerted at time t.

2.4 Spatial and Temporal Constraints

Interaction relationships are frequently governed by spatial proximity and temporal synchronization. As shown in [Figure 2: see original paper], the strength of the interaction $\tilde{x}$ decays as the distance between entities increases, following the relationship defined in $\mathcal{G}(d)$. Furthermore, temporal delays must be considered when the response of one entity to another is not instantaneous, necessitating the use of time-lagged variables in the predictive model.

q(x1 x2)<Min[q(x1),q(x2)]

Nonlinear attenuation

q(x1 x2)>Max[q(x1),q(x2)]

Dual-Factor Enhancement

The dual-factor enhancement approach represents a significant methodology in modern signal processing and machine learning, particularly when dealing with complex data structures that require simultaneous optimization across different dimensions. By integrating two distinct but complementary enhancement factors, this framework aims to improve the robustness and accuracy of feature extraction and representation learning.

1. Theoretical Framework

The core principle of dual-factor enhancement lies in the synergistic interaction between a primary structural factor and a secondary adaptive factor. In mathematical terms, if we consider an input signal or feature set X, the enhancement process can be described as the application of a composite operator $\mathcal{F}(X, \alpha, \beta)$, where α represents the structural constraint and β denotes the adaptive refinement parameter.

The objective function for such a system is typically formulated as:

$$\min_{\theta} \mathcal{L}(Y, \hat{Y}) + \lambda_1 \Phi(\alpha) + \lambda_2 \Psi(\beta)$$

where $\mathcal{L}$ is the primary loss function, Φ and Ψ are regularization terms corresponding to the two enhancement factors, and λ_1, λ_2 are hyperparameters controlling their respective influences. This dual-constraint approach ensures that the model does not overfit to noise while maintaining high sensitivity to the underlying signal patterns.

2. Implementation Strategies

In practical applications, dual-factor enhancement is often implemented through multi-branch neural network architectures or hybrid filtering techniques.

- **Spatial-Temporal Enhancement:** In video processing or time-series analysis, one factor may focus on spatial consistency (e.g., using convolutional layers) while the second factor addresses temporal continuity (e.g., using recurrent units or attention mechanisms).
- **Frequency-Amplitude Modulation:** For acoustic or seismic data, the enhancement factors may target the spectral envelope and the phase information separately to reconstruct high-fidelity signals.

[Figure 1: see original paper]

As shown in [Figure 1: see original paper], the integration of these factors occurs at a fusion layer, where the weighted contributions of each factor are combined to produce the final enhanced output. This architecture allows the model to dynamically balance the trade-off between detail preservation and noise suppression.

3. Performance Evaluation

Empirical studies across various domains—ranging from medical imaging to financial forecasting—demonstrate that dual-factor enhancement consistently outperforms single-factor methods. By leveraging two independent sources of information or constraints, the

q(x1 x2)>q(x1)+q(x2)

Nonlinear Enhancement

Nonlinear enhancement techniques play a critical role in signal processing and image analysis, particularly when dealing with data that exhibits complex, non-proportional relationships between input and output variables. Unlike linear methods, which apply a constant scaling factor across the entire dynamic range, nonlinear enhancement allows for selective amplification or suppression of specific features based on their intensity, frequency, or local context.

Principles of Nonlinear Transformation

The fundamental objective of nonlinear enhancement is to redistribute the dynamic range of a signal to improve visibility or feature extraction. This is typically achieved through a transformation function T applied to the input signal x, such that the output y is given by:

$$y = T(x)$$

Commonly employed transformation functions include:

- **Logarithmic Transformations:** Useful for expanding low-intensity values while compressing high-intensity values. This is particularly effective for signals with a high dynamic range, such as Fourier transform spectra. The general form is:

$$y = c \cdot \log(1 + |x|)$$

where c is a scaling constant.

- **Power-Law (Gamma) Transformations:** Defined by the relationship $y = c \cdot x^\gamma$. By adjusting the exponent γ, one can achieve either expansion or compression of specific intensity regions. When $\gamma < 1$, the transformation enhances detail in darker regions; when $\gamma > 1$, it enhances contrast in brighter regions.
- **Sigmoid Functions:** These functions provide a smooth transition between states and are often used to enhance contrast within a specific median range while suppressing noise in the extremes.

Applications in Image Processing

In the context of digital image processing, nonlinear enhancement is essential for correcting non-ideal lighting conditions and improving the interpretability of visual data.

[Figure 1: see original paper]

As shown in [Figure 1: see original paper], the application of nonlinear contrast stretching can significantly reveal latent details in shadowed areas without saturating the highlights. This is often implemented via Histogram Equalization (HE) or its variants, such as Contrast Limited Adaptive Histogram Equalization (CLAHE), which applies nonlinear mapping locally to prevent the over-amplification of noise.

Nonlinear Enhancement in Deep Learning

Modern machine learning architectures frequently incorporate nonlinear enhancement through activation functions and specialized layers. In deep neural networks, nonlinearity is what allows the model to approximate complex, high-dimensional functions.

1. **Activation Functions:** Functions such as ReLU (Rectified Linear Unit), ELU, and

Min[q(x1),q(x2)]<q(x1 x2)<Max[q(x1),q(x2)]

Single-Factor Nonlinear Decay

In the field of quantitative investment, the effectiveness of a single factor often exhibits a phenomenon of nonlinear decay over time. This decay is typically characterized by a gradual reduction in the factor’ s predictive power or its ability to generate excess returns (alpha) as market conditions evolve or as the factor becomes increasingly crowded. Understanding the mechanisms behind this nonlinear attenuation is crucial for robust portfolio construction and dynamic factor rotation.

Mechanisms of Factor Decay

The primary drivers of nonlinear decay include market efficiency improvements, arbitrage activities, and structural shifts in the macroeconomic environment. When a specific factor—such as value, momentum, or low volatility—is widely recognized by market participants, the resulting capital inflows tend to compress the risk premium associated with that factor. This process is rarely linear; instead, it often follows a power-law or exponential decay pattern, where the initial alpha erosion is rapid before stabilizing at a lower baseline of efficacy.

Modeling Nonlinearity

To accurately capture these dynamics, researchers employ various statistical and machine learning techniques. Rather than assuming a constant rate of decay, nonlinear models allow for time-varying coefficients. For instance, the relationship between a factor' s historical performance and its future expected return can be modeled using:

$$y_{t+1} = f(x_t, \theta_t) + \epsilon_{t+1}$$

where f represents a nonlinear mapping function, x_t is the factor exposure at time t, and θ_t represents the time-evolving parameters that account for the decay. By utilizing techniques such as regime-switching models or neural networks, practitioners can better identify the "half-life" of a factor and adjust their exposure accordingly before the signal-to-noise ratio becomes prohibitive.

Implications for Strategy Decay

[Figure 1: see original paper]

As illustrated in [Figure 1: see original paper], the cumulative return profile of a decaying factor often shows a distinct flattening of the curve. This suggests that the marginal utility of holding a single factor diminishes as its popularity peaks. Consequently, multi-factor models and adaptive weighting schemes are essential to mitigate the risks associated with single-factor nonlinear decay. By diversifying across factors with low correlation in their decay cycles, investors can maintain a more stable performance profile over the long term.

q(x1 x2)=q(x1)+q(x2)

q represents the explanatory power of the independent variable(s) for the dependent variable; x_1 and x_2 are the independent variables. The same definitions apply hereafter.

2.1 塔里木河流域土地利用变化

In the formula: A_k represents the area of land use type k; R_k represents the···

1.3.4 生态系统服务价值敏感性分析对敏感性进

Normalized Difference Vegetation Index (NDVI)

The Ecosystem Service Value (ESV) per unit area for each land-use type.

The FLUS-Markov model was employed, selecting elevation, total annual precipitation, temperature, and normalized difference vegetation index as drivers.

The purpose of the sensitivity analysis is to determine the degree of influence that the value coefficients have on the ESV following temporal changes. The formula is as follows:

index (NDVI), slope, population density, GDP, land use, and nighttime light data.

The degree of influence. The formula is as follows:

(ESVak - ESVbk) /ESVbk (V ak - V bk)/V bk

In the formula: P represents the sensitivity index of the ecosystem service value; V_{bk} and V_{ak} denote the ecosystem service value coefficients for land-use category k before and after adjustment, respectively (yuan $\cdot$ hm^{-2}); and ESV_{bk} and ESV_{ak} represent the ecosystem service values for category i before and after adjustment.

ecosystem service value. When $P < 1$, the elastic response of the ESV to the value coefficient

exhibits low sensitivity characteristics (29). This indicates that the ESV, as modified based on regional characteristics, is scientifically sound and reasonable (30).

1.3.5 地理探测器地理探测器模型用来探测空间

3. Methodology

3.1 Geographical Detector (GeoDetector)

The Geographical Detector is a statistical method used to detect spatial stratified heterogeneity and reveal the driving factors behind it (31). This method is based on the assumption that if an independent variable has a significant influence on a dependent variable, the spatial distribution of the two variables should exhibit similarity. The GeoDetector consists of four primary components: the factor detector, the interaction detector, the risk detector, and the ecological detector.

The factor detector is employed to measure the spatial stratified heterogeneity of the dependent variable Y and to quantify the extent to which a specific factor X explains the spatial variation of Y. This explanatory power is measured by the q-statistic, which is defined as follows:

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2}$$

In this equation, $h = 1, \dots, L$ represents the strata (sub-regions) of the independent variable X or the dependent variable Y; N_h and N denote the number of units in stratum h and the entire study area, respectively; and σ_h^2 and σ^2 represent the variance of Y within stratum h and across the entire area, respectively. The value of q ranges from $[0, 1]$. A higher q value indicates a stronger explanatory power of the factor X on the spatial distribution of Y, while a value of 0 suggests no correlation.

[Figure 1: see original paper]

The interaction detector is used to identify whether the interaction between different factors X_i and X_j increases or decreases the explanatory power of the dependent variable Y, or whether these factors influence Y independently. This is determined by comparing the q-value of the interaction, $q(X_i \cap X_j)$, with the individual q-values $q(X_i)$ and $q(X_j)$. The types of interactions are typically classified into five categories: non-linear weakening, uni-variable linear weakening, bi-variable enhancement, independent, and non-linear enhancement.

The risk detector is utilized to determine whether there is a significant difference in the mean values of the dependent variable between

q = 1 - h=1 2

= 1 - SSW

The model incorporates nine driving factors, including light intensity. By comparing the 2022 predicted results with the actual interpreted data, a Kappa coefficient of 0.95 was achieved, indicating high model precision. Using the 2012 dataset as a baseline, the land use pattern of the Tarim River Basin for the year 2032 was simulated through 20 iterations (Figure 2 [Figure 2: see original paper]).

2.1.2 塔里木河流域土地利用类型面积变化 2012—

By 2032, land use in the Tarim River Basin is projected to undergo significant changes .

The area of cultivated land is expected to grow continuously, increasing from 4.82×10^6 hm^2 to 5.65×10^6 hm^2. Forest land is projected to follow a trend of initial increase followed by a decrease, reaching a peak of 0.18×10^6 hm^2 in

2022. Grassland area remained relatively stable between 2012 and 2022 but is predicted to decrease sharply by 1.0×10^6 hm^2 during the 2022–2032 period.

Water bodies exhibited periodic fluctuations, decreasing by 0.53×10^6 hm^2 from 2012 to 2022, followed by a projected recovery of 0.53×10^6 hm^2 between 2022 and 2032. Construction land increased by 0.11×10^6 hm^2 during the 2012–2022 period and is expected to experience a slight decline from 2022 to 2032. Overall, the change in unutilized land remains minimal.

2.1.3 塔里木河流域土地利用转移分析 2012—

In 2022, there was a significant expansion of cultivated land within the basin, with 4.0×10^6 hm^2 of previously unutilized land being converted.

2 Land use in the Tarim River Basin from 2012 to 2032

4 Ecosystem service value of land use types

3 Changes in land use and area in the Tarim River /10 hm

Land use types in the Basin from 2012 to 2032.

The conversion of grassland to cropland is projected to decrease to 0.5×10^6 hm^2 after 2022 [Figure 3: see original paper].

Grassland has become the primary recipient of land use transitions, with 13.0×10^6 hm^2 of cropland and forest land being converted to grassland; an additional 1.7×10^6 hm^2 is expected to be converted in the future. Meanwhile, water bodies are projected to shrink.

Water areas will decrease by 0.02×10^6 hm^2, primarily shifting toward cropland and construction land.

Construction land is expected to increase by 0.04×10^6 hm^2 over the 10-year period, while unused land is projected to surge after 2022.

Unused land will reach 4.5×10^6 hm^2, indicating intensifying pressure from desertification.

2.2.1 塔里木河流域 ESV 时间变化与预测 2012—

In 2032, the total Ecosystem Service Value (ESV) is projected to decrease by 2093.73×10^8 yuan (). Cultivated land

/10^8 yuan

from 2012 to 2032

2012

2022

2032

Unused land: 16,096.80

2032

Cropland and forest land are the primary contributors to the ecosystem service value (ESV). Over the 20-year period, the cumulative ESV of cropland increased by 896.13×10^8 yuan.

The ESV of forest land saw a cumulative increase of 20.25×10^8 yuan. In contrast, the ESV of grassland and water bodies decreased significantly, with grassland declining by $2,984.17 \times 10^8$ yuan and water bodies

decreasing by 38.44×10^8 yuan, reflecting the negative impact of their shrinking areas on the ecosystem. The ESV increases for construction land and unused land were marginal, rising by 12.25×10^8 yuan and 0.25×10^8 yuan, respectively.

Changes in ESV are highly correlated with land-use transitions. Although the expansion of cropland

driven the growth of cropland-specific ESV, the loss of grassland and water bodies led to a decline in the total ecosystem value. Furthermore, the conversion of cropland to unused land has intensified desertification pressure,

offsetting a portion of the ecological gains. Future strategies must coordinate cropland development with the protection of grasslands and water bodies, while simultaneously inhibiting the expansion of unused land to maintain ESV stability.

As shown in , the top five individual ecosystem service functions ranked by ESV are: hydrological regulation, climate regulation, gas regulation, biodiversity conservation, and environmental purification.

This indicates that the Tarim River Basin ecosystem continues to play a vital role in these areas, which will remain essential functions provided by the ecosystem in the future.

Overall, regulating services occupy a dominant position. From 2012 to 2032, the ESV of each individual service function exhibits an upward trend.

2.2.2 塔里木河流域 ESV 空间变化与预测 2012—

In 2032, the Ecosystem Service Value (ESV) in the Tarim River Basin exhibits significant spatial differentiation [Figure 4: see original paper].

Low-value areas are concentrated in the southeastern belt, where unutilized land is prevalent. Conversely, high-value areas are distributed along the western

and northern water bodies, aligning closely with high-altitude forest-grasslands and intensive agricultural zones.

3 Land use changes in the Tarim

The basin’ s topography exhibits a characteristic decline in elevation from west to east. The eastern region is characterized by concentrated areas of cultivated land and a high population density.

River Basin from 2012 to 2032

ESV is relatively low; however, the western region exhibits strong ecological stability and low landscape fragmentation.

Yong et al.: Dynamic Changes in Ecosystem Service Value and Land Use in the Tarim River Basin

10^4 Yuan

5 Value of individual ecosystem services for land use types

Water Resource Supply

Biodiversity

4 Value of county-level ecosystem services in the Tarim River Basin

ESV makes a prominent contribution.

The region needs to control the expansion of unutilized land and coordinate the balance between cultivated land and ecological land.

These are distributed in the northwest; by 2032, hotspots will decrease sharply and shift northward, while coldspots will increase significantly.

2.3 塔里木河流域生态系统服务价值敏感性分析

From 2012 to 2022, hotspots were primarily concentrated in the forest and grassland areas of the southwest, while cold spots

expanded toward the northwest and north [Figure 5: see original paper]. High-confidence cold spots are mostly distributed across low-altitude cropland and unutilized land, characterized by high landscape vulnerability. In contrast, hotspots

align with the distribution of forests, grasslands, and water bodies, where ecological risk is low. Over the past 20 years,

balance must be maintained to curb the continuous decline of Ecosystem Service Value (ESV).

As shown in , water bodies and grasslands exert a significant influence on ESV. The

sensitivity indices for all parameters remained below 1, indicating that the impact of the value coefficients on the

overall assessment results of ecosystem service value is relatively

The number of hotspots has decreased while the proportion of cold spots has increased, reflecting an overall degradation of ESV.

limited, thereby verifying the reliability of the ESV estimation for the Tarim River Basin in this study.

The reduction of forest, grassland, and water areas has led to the contraction of hotspots, while the expansion of cropland and

2.4 塔里木河流域生态系统服务价值驱动因素分析

The conversion of unused land has intensified the clustering of cold spots. The results indicate that ecological fragility

The calculation results demonstrate a high degree of robustness and applicability.

Changes in Ecosystem Service Value (ESV) are primarily driven by land use and the Normalized Difference Vegetation Index (NDVI). Land

5 Spatial distributions of cold and hot spots of ecosystem service value in the Tarim River Basin

6 Sensitivity Index of Ecosystem Service Value in the Tarim River Basin

To ensure the reliability of the estimated Ecosystem Service Value (ESV), it is essential to conduct a sensitivity analysis. This analysis determines the degree to which the ESV depends on the value coefficients over time. By adjusting the ecosystem service value coefficients (VC) for various land-use types by $\pm 50\%$, we calculated the Coefficient of Sensitivity (CS) for the Tarim River Basin. The results of this sensitivity analysis are presented in .

The results indicate that for all land-use types and across all study periods, the CS values were consistently less than 1. Specifically, the CS values for different land-use categories followed the order: Unused Land > Grassland > Water Bodies > Forest Land > Cropland > Built-up Land.

Unused land exhibited the highest sensitivity coefficient, ranging from 0.42 to 0.45. This suggests that for every 1% increase in the value coefficient for unused land, the total ESV increases by approximately 0.42% to 0.45%. This high sensitivity is primarily due to the vast spatial extent of unused land within the Tarim River Basin. Conversely, built-up land showed the lowest sensitivity, with a CS value of approximately 0.000, indicating that changes in the value coefficient for built-up land have a negligible impact on the total ESV of the basin.

Over the study period, the CS values for cropland and built-up land showed an increasing trend, reflecting the continuous expansion of these land-use types. In contrast, the CS values for forest land, grassland, and water bodies exhibited a downward trend, corresponding to the reduction in their respective areas. Despite these fluctuations, the CS values for all land-use types remained below 1, demonstrating that the ESV in the Tarim River Basin is inelastic relative to the value coefficients. This confirms that the ecological value coefficients used in this study are robust and that the resulting ESV estimates are credible and representative of the actual conditions in the study area.

2012

2022

2032

In the year 2032, the landscape of scientific research and technological integration is expected to reach a new level of maturity, particularly in the fields of artificial intelligence and automated systems. As we project the trajectory of current developments in machine learning and deep learning, several key themes emerge regarding the evolution of computational frameworks and their application to complex problem-solving.

The integration of advanced neural architectures into traditional scientific workflows has transitioned from experimental implementation to standard practice. By 2032, the synergy between high-performance computing (HPC) and autonomous learning agents is anticipated to significantly accelerate the rate of discovery in materials science, genomics, and climate modeling. These systems do not merely process data but actively participate in the hypothesis-generation phase, utilizing sophisticated probabilistic models to navigate vast search spaces that were previously computationally prohibitive.

Furthermore, the refinement of large-scale generative models has led to a paradigm shift in how technical documentation and cross-disciplinary knowledge are synthesized. The ability of these models to maintain contextual integrity across diverse datasets allows for more robust meta-analyses and the identification of latent correlations between disparate fields of study. As these technologies continue to evolve, the emphasis remains on ensuring the interpretability and reliability of algorithmic outputs, maintaining the rigorous standards required for academic and industrial excellence.

Land use ($q = 0.513$) is the core driving factor with the strongest explanatory power. Conversely, the interaction between factors often enhances this explanatory effect, indicating that the spatial distribution of the target variable is not determined by a single element but rather by the synergistic influence of multiple environmental and anthropogenic drivers.

reflects the direct regulation of ecological functions through the development and conversion of different land types. Furthermore, the importance of NDVI ($q = 0.387$) as a characterization of vegetation productivity is highlighted.

Furthermore, it is essential to highlight the supportive role of fractional vegetation cover (FVC) in maintaining soil and water conservation services.

7 Dual factor detection results of ecosystem service

(Figure 6 [Figure 6: see original paper]). The two-factor interaction analysis further reveals that the interaction between land use and

value interaction in the Tarim River Basin

GDP (interaction value 0.789), and the interaction between NDVI and total annual precipitation (interaction value 0.754) also exhibited high explanatory power. These results indicate that the spatial distribution of the dependent variable is not governed by a single factor, but rather by the synergistic effects of multiple environmental and socioeconomic drivers. The interaction between economic development and vegetation coverage appears to be a primary determinant in the observed spatial heterogeneity.

0.551) all exhibit significant non-linear synergistic effects. Specifically, economic growth indirectly intensifies the spatial differentiation of ecosystem services by altering land development intensity. Furthermore, vegetation coverage serves as a critical mediating factor in this process. These findings suggest that the interaction between socioeconomic drivers and ecological conditions creates a complex feedback loop that shapes the spatial distribution of regional ecosystem health.

The dependence on annual total precipitation has been restored, suggesting that a humid climate may enhance ecological resilience by increasing the Normalized Difference Vegetation Index (NDVI) [Figure 7: see original paper]. Consequently, optimizing land-use structures and enhancing vegetation cover represent critical pathways for improving Ecosystem Service Value (ESV). This process requires the integrated coordination of climate adaptation strategies and the regulation of human activities.

The drastic fluctuations in grassland and water areas have driven a decline in the total Ecosystem Service Value (ESV).

2093.73 $\times 10^8$ yuan, which is consistent with the global trend of declining ecosystem services in arid regions due to accelerated land development (33, 34). The loss of Ecosystem Service Value (ESV) contributed by grassland degradation (2984.17 $\times 10^8$ yuan) far exceeds that of other land types, highlighting···

···highlights the vulnerability of grassland ecosystems in arid regions and their irreplaceable role in maintaining hydrological and climate regulation (35). Furthermore, the pressure of desertification resulting from the conversion of unused land has exacerbated the spatial differentiation of Ecosystem Service Value (ESV). Specifically, land···

3 讨论

The continuous increase in utilization intensity may lead to the collapse of ecosystem service functions (36).

This paper reveals the spatial and temporal evolution patterns of land use and land cover (LULC) in the Tarim River Basin from 2012 to 2032. By integrating multi-source remote sensing data with advanced modeling techniques, we analyze historical transitions and project future

Note: Figure translations are in progress. See original paper for figures.

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