Characteristics of Spatial and Temporal Land Use Changes, Driving Factors and Development Trend Prediction

-- Taking the Three Northeastern Provinces as an Example

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Abstract. Urbanization and economic development have reshaped the production and living needs of the population, making land-use planning and forecasting increasingly critical for national development. Currently, the issues related to land use in the three northeastern provinces of China remain inadequately defined. This study focuses on these provinces, investigating the spatial and temporal patterns of land-use change, the driving factors influencing land-use types, and future development trends. By analyzing data from the National Bureau of Statistics, the Chinese Academy of Sciences, and the Institute of Geography, among others, and applying the PLUS model, Markov chains, and ArcGIS spatial analysis techniques, the study yields the following conclusions: (i) The influence of different driving factors on the expansion of various types of land in the three northeastern provinces has obvious differences, among which the influence of GDP on construction land is particularly significant. (ii) Under the double influence of national strategy and the background of the times, the land use of the three northeastern provinces has been transformed, with arable land and residential land, construction land expanding in the central plains; and forests converting into the peripheral mountainous areas, especially in the northern forested areas with a particularly significant trend. (iii) The likelihood of conversion of different land-use types varies, with cropland and forest land in general not changing much. In contrast, the probability of conversion of grassland and other construction land is as high as 50%, and unutilized land is also subjected to a considerable degree of development. Only about 20% of urban and rural residential land is likely to change, but there is a clear trend of conversion between the two. (iv) Generally speaking, there will be little change in land use in the study area in the next 10 years. Under the influence of “returning farmland to the forest”, arable land will shrink in the Sanjiang Plain and Songnen Plain, and the area of ecological land will grow significantly; further population growth will trigger urbanization and residential migration in the suburbs, and the sustainable development of food, environment, and population will be realized step by step.

Keywords: PLUS Model; Three Northeastern Provinces; Markov Chain; Land Use; Future Prediction; Driving Mechanism.

1. Introduction

Against the backdrop of accelerating economic globalization and regional economic integration, land use patterns are undergoing profound changes. Factors such as population growth, urban expansion, industrialization, and climate change are placing unprecedented pressure on land resources. These changes not only affect the health of natural ecosystems but also have far-reaching impacts on socio-economic structures [1-5]. Exploring land use in the global context is not just about understanding and addressing the environmental and social challenges we face today but also about exploring pathways toward sustainable development.

Land use refers to the human-driven processes of developing, transforming, and conserving land resources based on societal needs. Over the past few decades, an increasing number of countries, international organizations, and NGOs have advocated for the formulation of new land legislation and policies that formally recognize collectively owned land and previously neglected natural resources [6]. Land use in today’s world is no longer confined to specific regions or countries; it has become a global issue that transcends national borders and involves multiple interests. It is closely linked to the quality of the human living environment, sustainable economic and social development, and the health of the global ecosystem [7]. Agricultural plantations of multinational corporations, the flow of agricultural products in international trade, and the impact of global climate change on land use patterns have all elevated land use to a critical field of international study [8].

Land use is not only a key concern for governments but also a significant challenge for the global community. As the world population grows and urbanization accelerates, many regions are experiencing the strain of unsustainable land use, highlighting emerging conflicts and contradictions [9,10]. More arable land is needed for agricultural production to ensure food security and protect farmers' rights, while industrialization and urbanization continue to encroach upon agricultural lands [11]. Furthermore, the increasing frequency of extreme weather events linked to climate change has exacerbated pressures on land resources; overgrazing and poor agricultural practices have led to soil erosion; and the reduction of green spaces during urbanization has intensified the urban heat island effect, contributing to a host of urban problems [12,13]. These phenomena not only threaten ecological security but also affect food security, water resource management, and socio-economic stability.

Land is a critical element of human livelihood, serving not only as the material foundation for survival and development but also as a key driver of economic activities [14]. The study of land-use change is a central focus of global research, encompassing changes in ecosystem services, biodiversity conservation, and the pursuit of sustainable development goals [15]. The transformation of key agricultural areas, particularly the shift between agricultural and non-agricultural land, plays a crucial role in food security. Land use changes in these critical regions directly affect food reserves, water resource management, and environmental quality. Therefore, a thorough exploration of land use changes in these areas is vital for ensuring national food security and promoting balanced regional development.

In the face of these global challenges, it is crucial to address land use issues rationally and effectively. By utilizing geographic information systems (GIS), remote sensing technology, predictive modeling, and other advanced tools, we can better understand the trends in land use change and its impacts on both the environment and society [16, 17]. These studies will not only help identify the driving factors behind land use changes but also provide a foundation for developing evidence-based land management policies. Furthermore, they will support the achievement of sustainable development across the economic, social, and environmental dimensions, fostering a future where humanity coexists harmoniously with nature.

2. Related Work

Currently, numerous studies have been conducted in the field of land use, and the discourse surrounding the driving factors influencing land use types has become more comprehensive. Li et al. performed an extensive analysis of the evolutionary stages, research hotspots, dynamic processes, and key components of land ecological security assessment studies in the context of climate change, employing entropy weighting, ecosystem services, indicator systems, and object-element modeling [18]. Xu et al. integrated a simple global socio-economic model (GLOBFOOD) with a regional spatial allocation model (CLUE) to develop a unified modeling system aimed at simulating the impacts of the global market and economy on land use [19]. Moreover, Luo et al. utilized the PLUS model to simulate future land cover (LULC) scenarios and the InVEST model to assess the environmental effects of rapid GDP growth in Guiyang City [20].

Satellite remote sensing technology plays a crucial role in supporting land use and land cover (LULC) data. Liu et al. established a land use remote sensing classification system and corresponding coding framework based on existing classifications of land cover derived from multi-resolution remote sensing data, which were subsequently integrated [21]. The theoretical models and technical tools for land use simulation and prediction have become relatively mature. Kabanda monitored land cover type changes through remote sensing techniques and Markov chains [22-24]. The Conversion of Land Use and its Effects at Small Regional Extent (CLUE-S), a small-scale land use simulation model developed by the “Land Use Change and Effects” research group at Wageningen University in the Netherlands, is widely used for land prediction. The CLUE-S model, with approximately 30 applications in various regions worldwide, effectively demonstrates the trajectory of land use change and enables future predictions [25]. Liu et al. used results from SPSS-Logis regression analysis to construct the CLUE-S model and forecast the land use pattern in 2017 [26]. Kiziridis et al. improved the model by introducing the trans-CLUE-S model, which reduced both the overall and configurational inconsistencies of the CLUE-S model by approximately 50%, enhancing the reproducibility, transparency, and accuracy of land cover change modeling and interpretation [27]. Zhang et al. also employed this model to simulate land use changes in the agro-pastoral zone under four scenarios [28]. However, this model primarily focuses on smaller areas, making it challenging to simulate more complex large-scale land use scenarios accurately. He et al. developed the Land Use Scenario Dynamics (LUSD) model by combining the System Dynamics (SD) model with the Cellular Automata (CA) model to simulate land use [29]. However, parameter calibration remains difficult, and there is a lack of a unified and standardized methodology. Haney et al. predicted the dynamic changes in cropland areas between 2005 and 2050 using the Global Land Use Dynamics Model (GLUDM) [30]. Nonetheless, the high uncertainty of global land use and external factors makes accurate predictions challenging. Li et al. used the PLUS model and InVEST model to assess the correlation between habitat quality and land use change, which is an innovative approach, but with limited applications; therefore, its empirical accuracy requires further validation [31].

In summary, current research on land use prediction has not yet kept pace with the evolving demands of theory and practice. Geographic elements and environmental conditions have undergone significant changes in the Internet era, necessitating improvements in the adaptability, matching precision, and operational efficiency of existing land use simulation models. Furthermore, large-scale and multi-category land-use simulations require vast data resources, making the process more complex. The lesser-used PLUS model, however, offers high-precision patch-level simulations and an adaptive modeling mechanism, bringing results closer to real-world conditions [32]. When selecting driving factors for land use types, most studies focus on single factors, lacking a macro-integrated perspective, which can lead to one-sided or overly simplified conclusions. Additionally, current research on land use change and prediction is mainly concentrated in the northern regions, Shanghai, Guangzhou, Shenzhen, provincial capitals, and economically developed urban agglomerations, with limited attention paid to Northeast China. There are few studies focused on this region, especially regarding the systematic analysis of dynamic land use changes in Northeast China using the PLUS model. However, experiences differ across cities, and land use change is not universally applicable. As the revitalization strategy for Northeast China progresses, the region's valuable land resources require more focused attention. This study aims to address these gaps by analyzing spatial and temporal land use changes over the last two decades in the three northeastern provinces using the PLUS model and Markov chain, uncovering the driving mechanisms and inherent patterns of change. It also seeks to predict future land use trends based on historical data. Complemented by spatial data analysis through geographic information technology (GIS) and statistical methods to assess the influence of various driving factors, this study will provide an in-depth exploration of land use transformation in the three northeastern provinces. This research not only enhances our understanding of the current land use situation in Northeast China but also serves as a reference for developing adaptive land management strategies in other regions. It is of significant practical importance for the formulation of scientific, rational land management and ecological protection policies, contributing to the establishment of a more sustainable and scientifically grounded land use pattern.

3. Materials and Methods

3.1 Research Area

The three northeastern provinces of China—Liaoning, Jilin, and Heilongjiang—are located between 120°E and 135°E longitude and 40°N and 53°N latitude, covering a total area of 787,300 km². The region's topography is dominated by plains and mountains, with the northeastern plains serving as a key agricultural area (Figure 1) [33]. Rich in natural resources, the Northeast boasts unique climatic conditions and a strong industrial base, making it an important industrial and food production hub in China. It occupies a pivotal position not only within China but also in Northeast Asia [34].

According to national census data, the population of the three northeastern provinces has declined by approximately 11 million people over the past decade, representing a reduction of about 10%, highlighting significant demographic challenges. By 2024, the total resident population of the Northeast has decreased from a peak of 110 million in 2010 to around 95 million, continuing its downward trend. The total GDP of the three provinces is comparable to that of Bangladesh, and the region's GDP growth rate lags behind the national average, exacerbated by issues such as a monolithic economic structure, outdated state-owned enterprises, and insufficient innovation capacity [35]. In response, the Chinese government has recognized the importance of revitalizing the Northeast and has actively implemented targeted strategic planning to inject new momentum into the region's development, thereby enhancing China's global influence.

With its abundant natural resources, vast arable land, and strategic geographic location, Northeast China has become an ideal region to study land use change and its driving factors, both within China and globally [36]. The development of agriculture in the Northeast is among the highest in the country, owing to its fertile black soil, rich in nutrients and ideal for crop cultivation. However, like many other regions worldwide, land use research in the three northeastern provinces faces challenges, including difficulties in obtaining land use data, complex land use structures, ecological degradation, and the urgent need for effective regional land planning [37].

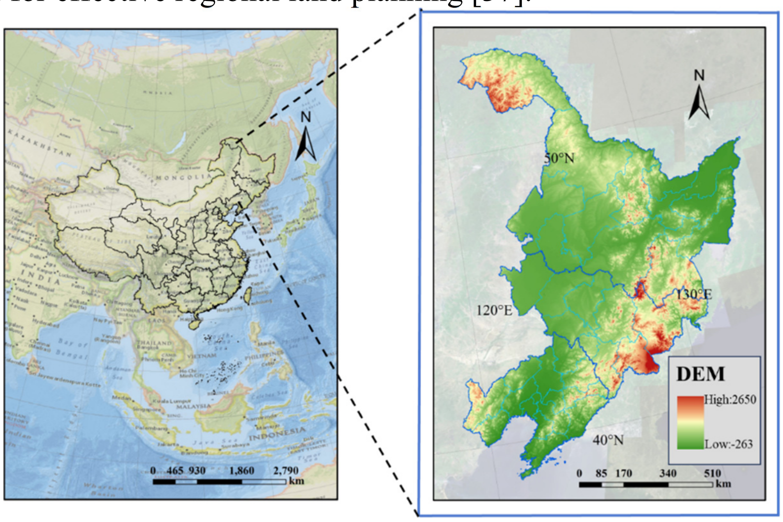


Figure 1. The geographical location of the Northeast China

As a major food production base in China, the region's land use pattern has undergone subtle but significant changes over the past few decades, driven by shifting social and economic demands. These changes have led to frequent conversions between different land use types, creating tensions between economic development and resource conservation. This dynamic is not linear, but rather a non-linear process influenced by the fluctuating natural and socio-economic conditions of the region. Such changes have not only affected the quality of the local ecological environment but also have significant implications for the sustainability of agricultural production and the future trajectory of the region's economic development. Therefore, the three northeastern provinces are analyzed as a case study to predict the evolution of various land use types and forecast future development trends, aiming to offer valuable insights into regional land use dynamics and ultimately supporting the development of more sustainable and balanced land management policies.

3.2 Data Sources

The geographic data utilized in this study are publicly available, mostly in the form of raster data, of which the land use type data for 2015 and 2020 are derived from the 30-m precision LUCC data of the Chinese Academy of Sciences (http://www.igsnrr.cas.cn/kjpt/ptzc/sjpt/). This dataset is one of the few 30m resolution long time series land use and land cover change (LUCC) datasets available in China today. Based on the National Resources and Environment Database (NRED), the Chinese Academy of Sciences (CAS) has established a national-scale 1:10 scale multi-period land use/land cover remote sensing monitoring database (CNLUCC) by using Landsat remote sensing imagery data as the main information source and manual visual interpretation.

The administrative area boundary data of the three northeastern provinces were adopted from the 2019 China Map Vector Data (Cartographic Review: GS(2019) 1822).

Data on various land expansion drivers and their detailed sources are presented in Table 1.

Table 1. Research materials

Category	Name	Usage	Source
Geographic data	Temperature Precipitation Soil type DEM Water vector data	The driving factors of land-use expansion	Geospatial Data Cloud, CAS (http://www.igsnrr.cas.cn/kjpt/ptzc/sjpt/) https://www.gscloud.cn/ Open Street Map(OSM) platform (https://foursquare.com/about/osm)
Socio-economic indicators	GDP Population density Road vector data (Residential, Commercial, Service, etc.) POIs	The driving factors of land-use expansion	Geospatial Data Cloud, CAS (http://www.igsnrr.cas.cn/kjpt/ptzc/sjpt/) Open Street Map(OSM) platform (https://foursquare.com/about/osm) AutoNavi-map development platform (https://www.amap.com/)

3.3 Research Methodology

3.3.1 ArcGIS Strategy

ArcGIS is a suite of geographic information system (GIS) software developed by Esri for creating, managing, analyzing, and sharing spatial data [38]. As an integrated platform, it offers a variety of tools and applications for data visualization, map production, geographic analysis, and collaboration [39].

ArcGIS supports a broad range of data formats and sources, making it widely applicable in fields such as urban planning, environmental management, and transportation [40]. Major components of the platform include ArcGIS Online, ArcGIS Pro, and ArcGIS Enterprise. These tools enable users to perform efficient geographic data analysis and decision support, facilitating map production and geographic information management across multiple devices and environments, including desktop computers, mobile devices, and web applications. In this study, ArcGIS leverages its specialized computing tools for geographic data preprocessing, enabling users to standardize the projected coordinate system and raster format and to clearly and accurately represent land use simulation results.

3.3.2 PLUS Model

The PLUS model, a tool for simulating urban sprawl, is widely used in various studies, such as land planning and management and the quantitative assessment of ecosystem services during the urbanization process [41, 42]. Based on the rule mining framework of the Land Expansion Analysis

Strategy (LEAS) and the Cellular Automata model with multiple stochastic seed types (CARS), the model integrates a variety of influencing factors (e.g., population density, GDP, temperature, precipitation) and is capable of effectively simulating and predicting future land expansion [43]. When applied to the three northeastern provinces, the PLUS model provides a comprehensive understanding of the changing patterns of regional land use.

The LEAS framework employs the Random Forest algorithm to calculate the contribution of various driving factors to land use changes, the error value, and, based on this, the probability of land use type changes.

The widely adopted calculation formula is as follows:

$$P_{i,k}^{a}(x) = \frac{\sum_{n=1}^{N} I(h_n(x) = a)}{N} \tag{1}$$

Where *P(x)* is the expansion potential of each land use type. *a* takes the value of 0 or 1: a value of 1 means that the existing land use type will be shifted to land use type *k*, and 0 means that the original land use type will be maintained. *X* denotes a vector consisting of multiple drivers. *I(*)* serves as an indicator function in the set of decision trees, and $h_n(x)$ denotes the prediction result of the nth decision tree by the input vector *x*, *N* corresponding to the number of decision trees.

The CARS model refers to the Cellular Automata (CA) model that incorporates a seeding mechanism based on multi-type stochastic patches. Its primary purpose is to simulate the spatial evolution of different land use patches, thereby enhancing existing land use simulation models and improving their accuracy in predicting regional land use changes [44]. The model treats each grid cell as a processing unit, simulating land use changes by setting parameters such as restricted areas for land change, neighborhood weights, and others, and calculating the likelihood of various land use types occurring within each grid cell [45].

To simulate temporal changes in multiple land use types, this study utilized the CARS model developed by Liang et al. The computational process involves estimating the overall probability of change [46]. The model was implemented using the Monte Carlo method to simulate the development of patches of different land use types, considering various constraints and neighborhood effects specific to each land use type, as follows:

$$OP_{a,b}^{d=1,t} = \begin{cases} P_{a,b}^{d=1} \times (\mathrm{r} \times \mu_b) \times A_b^t & if\ \Omega_{a,b}^t = 0\ and\ r < P_{a,b}^{d=1} \\ P_{a,b}^{d=1} \times \Omega_{a,b}^t \times A_b^t & all\ others \end{cases} \tag{2}$$

where *r* is a randomly generated value in the range 0 - 1, *Ω* denotes the neighborhood effect of the cell, and μ_b is a user-defined threshold for the generation of new land-use patches by the land-use type *b*. These generated seeds have the potential to evolve into new patches. *A* is an adaptive value.

The PLUS model proposes a decreasing threshold rule for the competitive process for all land use types. If a new land use type wins a round of competition, the model determines whether the area of land use of that type meets the estimated demand, and accordingly determines whether to stop.

3.3.3 Markov Chain

A Markov chain is a set of discrete random variables with the Markov property, i.e., no memory, and the random variable at step t+1 is conditionally independent of the rest of the random variables given the random variable at step t. Markov chains can be applied to Monte Carlo methods [47]. In this paper, we chose to utilize a Markov chain to determine the land-use demand in the target year, which is calculated as follows:

$$p(X_{k+1} \mid X_{k, \ldots\ldots,} X_1) = p(X_{k+1} \mid X_k) \tag{3}$$

$$P_{d,d+1} = (P_{i_d, i_{d+1}}) = \begin{bmatrix} P_{0,0} & P_{0,1} & P_{0,2} & \cdots \\ P_{1,0} & P_{1,1} & P_{1,2} & \cdots \\ P_{2,0} & P_{2,1} & P_{2,2} & \cdots \\ \cdots & \cdots & \cdots & \cdots \end{bmatrix} \tag{4}$$

where X_k is a set of random variables. $P_{m,n}$ is the transfer from land use type m to land use type n. Eq. 4 is the transfer matrix.

The Markov transfer matrix, also known as the state transfer matrix or leapfrog matrix, is an important component in a Markov chain. Each element p_{ij} in the transfer matrix represents the probability that the system will transfer from state i to state j. The transfer matrix is a square matrix with the number of rows and columns equal to the number of possible states of the system. Each row of the matrix represents a probability distribution of transfers from a particular state to all other states so that the sum of the elements in each row is 1 [48].

Markov transfer matrices can be used not only for land-use type conversion, but also in a wide range of fields such as stock price prediction in financial markets, DNA sequence analysis in biology, natural language processing, and many other fields, where the distribution of a system's state after multiple future time steps can be predicted through multiple applications of transfer matrices (i.e., the powers of the matrices) [49, 50].

4. Model Construction and Validation

4.1 Regional Environment Modeling

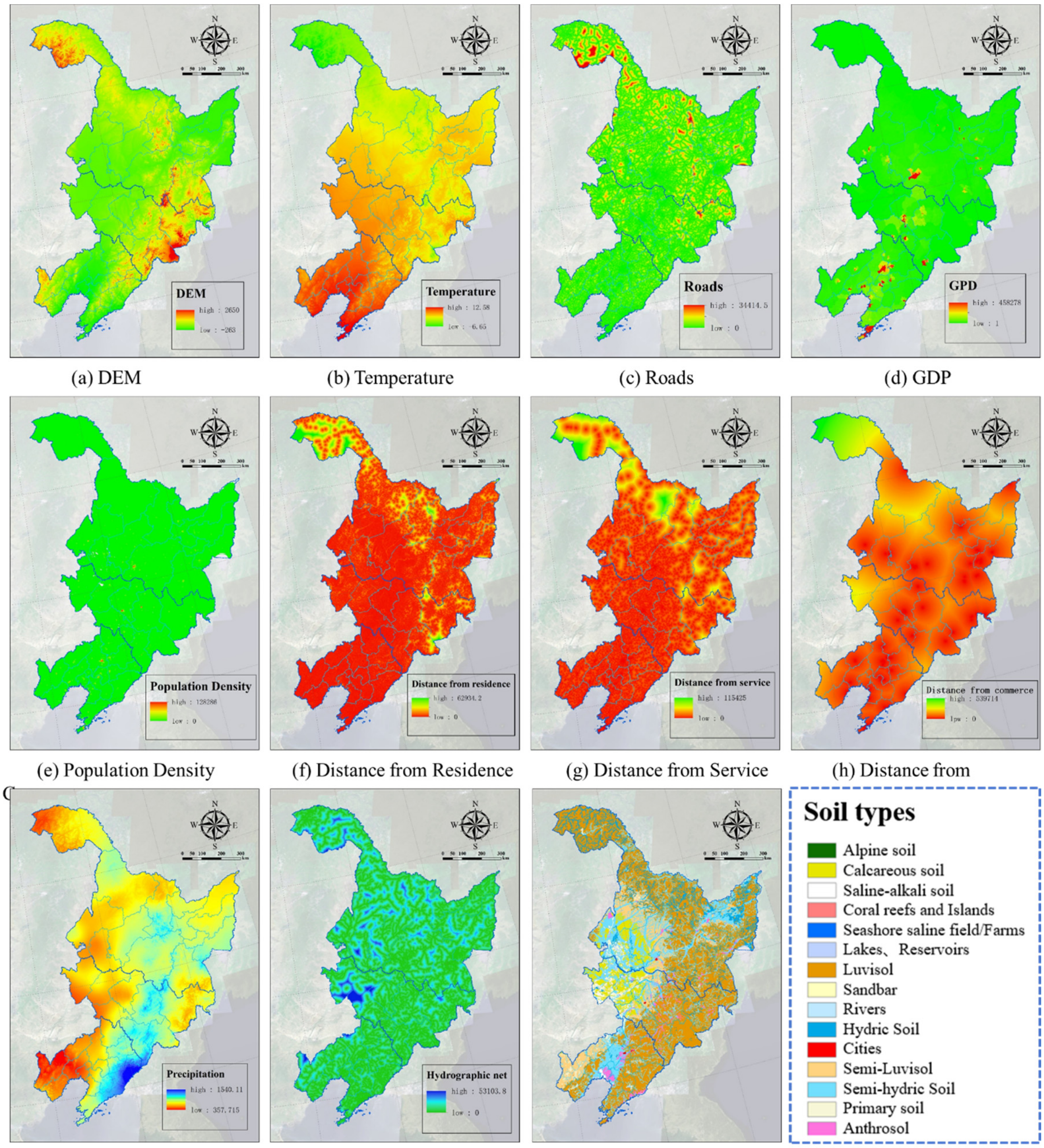
Land use types are influenced by a variety of driving factors, and eleven driving factors are selected in this study to construct the land expansion atlas. As shown in Figure 2, the climate of Northeast China exhibits a distinct spatial pattern. Temperature decreases from south to north, following the latitudinal zonal law, with the Mohe River being the coldest location in China [51]. Temperature is also lower in the Changbai Mountains and the Great and Small Xing'an Mountains, which are situated at higher altitudes. Precipitation generally decreases from southeast to northwest due to the land-sea distribution and monsoon influences, with the rain shadow areas of the mountain ranges receiving less rainfall.

The central region of Northeast China is characterized by flat terrain, rich in fertile leachate and weak leachate soils. The area's ecological conditions—cold, humid climate, fertile soil, and an extensive water network—are highly conducive to vegetation growth. These conditions support the cultivation of high-quality crops, which in turn benefit agricultural development, urban expansion, and infrastructure construction. In contrast, the peripheral mountain ranges are rich in forest resources, creating an environment favorable for the development of the fruit and forest economy.

Soil types in the study area are diverse, with leachate and weak leachate soils being predominant. Hydric soils are commonly found in low-lying lakes, swamps, and other wetlands. In semi-moist, semi-arid areas near the inland, calcium carbonate deposition leads to the formation of calcareous soils, which are susceptible to drought, wind, and sand erosion, necessitating the rationalization of agricultural and pastoral activities.

The spatial distribution of urban infrastructure, road networks, and socio-economic indicators in the three northeastern provinces centers around major cities such as Shenyang, Dalian, Changchun, and Harbin, with these cities serving as prominent hubs radiating outward. The surrounding prefecture-level cities are key nodes in the network. The spatial distribution of shopping, service, and residential facilities is highly concentrated around these central cities, catering to the needs of the primary population, with a notable correlation to the first law of geography [52]. However, the Northeast region lags in overall economic development. Population density is low, with a significant concentration in a few major cities, leading to a phenomenon of outward migration. Furthermore, socio-economic indicators display considerable regional disparities, and the northernmost regions suffer from a relatively low level of urban development. These areas also lack adequate residential, commercial, and service facilities to meet the diverse needs of the population, highlighting the urgent need for policy intervention and industrial restructuring.

In recent years, the three northeastern provinces have actively pursued the development of "new quality productivity" and innovative economic models, alongside the development of social support services [53]. Additionally, leveraging the strong growth momentum of Dalian's foreign trade and imports/exports has accelerated the region's opening up to the broader national and global markets.



(a) DEM (b) Temperature (c) Roads (d) GDP

(e) Population Density (f) Distance from Residence (g) Distance from Service (h) Distance from

C

(i) Precipitation (j) Hydrographic nets (h) Soil types

Figure 2. Driving factors of land use change

4.2 LEAS Model Training and Testing

The Land Extension Analysis Strategy (LEAS) model utilizes a sampling method for model training, with Root Mean Squared Error (RMSE) used to evaluate the training performance, while Out-of-Bag Root Mean Squared Error (OOB RMSE) assesses the model's generalization ability.

The random forest training results are shown in Figure 3, where most of the RMSE values are below 0.1, indicating strong training performance and accurate predictions for the sample data.

However, it is worth noting that the RMSE for both cropland and forest exceeds 0.1, with the OOB RMSE values surpassing 0.3. This discrepancy may be attributed to the instability of meteorological factors, which restrict the expansion of woodland and grassland. In contrast, the predictions for urban and rural residential land, as well as construction land, are more accurate. The choice of search step and the classification of ecological and construction land in the land image element also influence the error values.

In summary, the LEAS sub-model demonstrates strong training and generalization capabilities, providing a solid foundation for calculating land expansion potential.

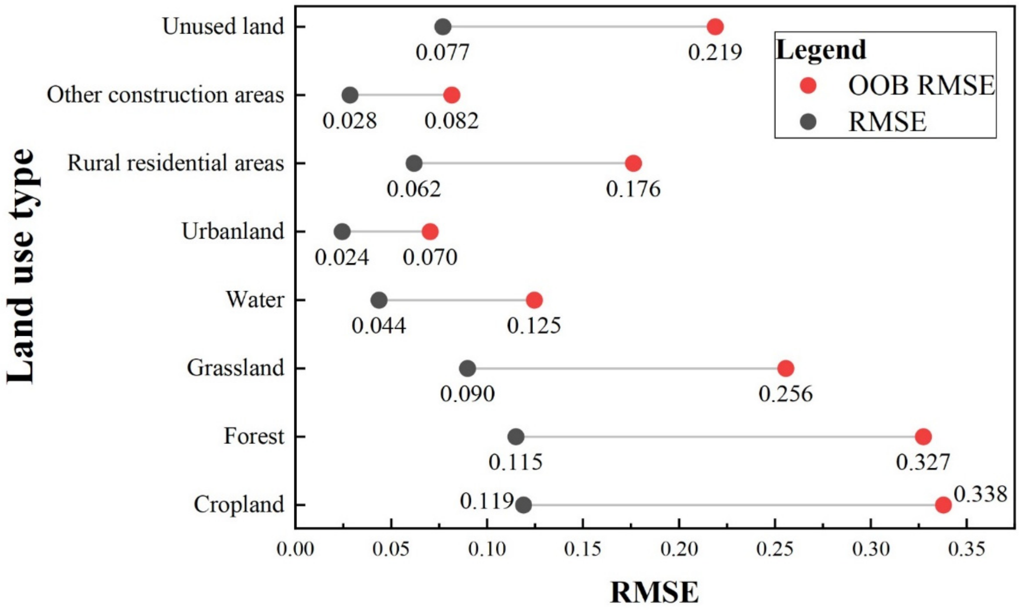


Figure 3. LEAS model training results

5. Results and Discussion

5.1 Land Expansion

Northeast China is one of the most important agricultural production bases in China, rich in natural resources, particularly fertile black soil. The land use patterns in this region are representative of the broader northern China context [54]. As shown in Figure 4, the land use types in Northeast China are primarily dominated by forested land and arable land, with a relatively balanced ratio between agriculture and animal husbandry. The expansion of arable land is most concentrated in flat, open areas such as the Northeast Plain, Songliao Plain, and Sanjiang Plain, with the most significant changes observed in the Sanjiang Plain. In contrast, forests are predominantly found in mountainous regions, with their expansion areas primarily located in the surrounding mountain ranges, such as the Changbai Mountains and the Great and Small Xing'an Mountains. Grassland expansion is mainly concentrated in the western areas bordering Inner Mongolia [55].

Between 2015 and 2020, land use types in the three northeastern provinces underwent notable changes. Forest area expansion in the northern regions was particularly significant, while the fragmentation of ecological land use decreased, contributing to a more cohesive ecological landscape. Additionally, a new body of water emerged in the northern region, which is initially hypothesized to be a result of increased water volume at the confluence of the Heilongjiang, Songhua, and Ussuri rivers, possibly due to recent climate warming trends. Over the past decade, cultivated land in the plains has expanded substantially, while pastureland, construction land, and residential areas have also undergone varying degrees of change. Furthermore, previously unutilized land has been increasingly opened up.

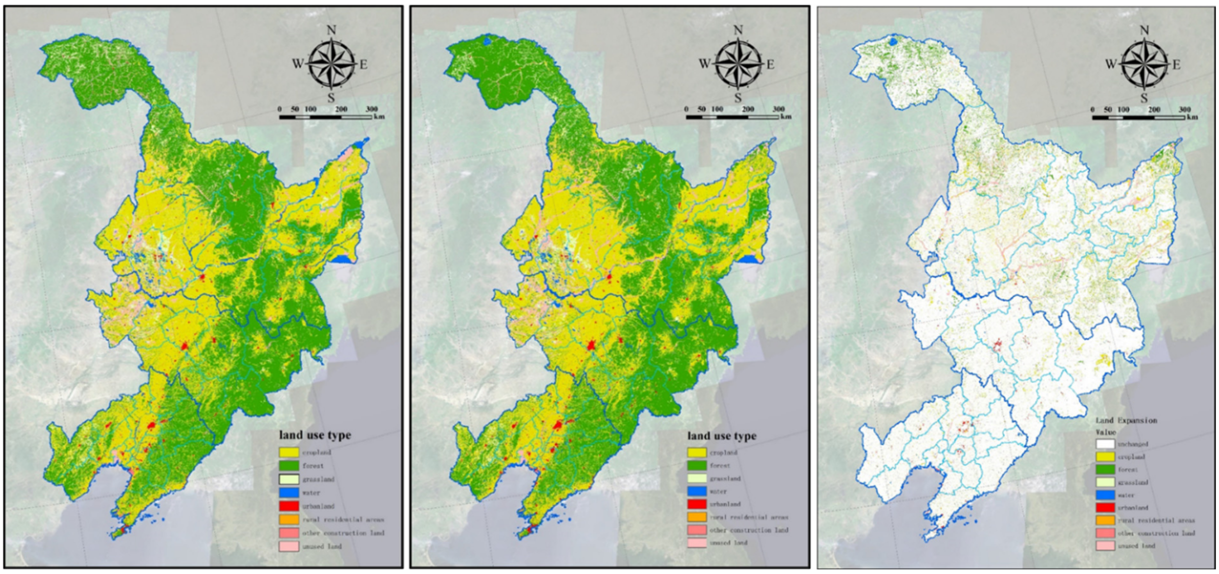


Figure 4. Changes in land use types, 2015-2020

5.2 Analysis of the Driving Factors of Land Expansion

Figure 5 illustrates the percentage contribution of various drivers to land expansion, as calculated by the random forest model. The analysis of these drivers is fundamental for estimating the probability of expansion across different land use types and for guiding land development planning.

Climatic conditions (temperature and precipitation) and elevation are the primary factors influencing the expansion of arable land. Additionally, socio-economic factors, particularly GDP, exert a significant influence on regional arable land expansion [56]. As shown in the figure, arable land in the Northeast region is predominantly located in areas with superior natural resources, often in proximity to population centers, to meet the needs of daily life and economic development. Other ecological land use types are primarily influenced by natural factors, with precipitation playing a crucial role in limiting their expansion.

Rapid urbanization in the three northeastern provinces has driven the expansion of urban and other construction land. GDP is the most significant controlling factor, contributing 30% to urban land expansion and 20% to construction land expansion. Moreover, population density and the availability of social service facilities (including commercial, service, and residential facilities) also play a major role in the expansion of urban and construction land.

The expansion of rural residential land is closely linked to population density and the availability of services and residential facilities. The contribution of residential facilities to rural residential land expansion is 18%, but the influence of commercial facilities and GDP is considerably lower than in urban areas. In rural regions, population density and service facilities (e.g., schools, hospitals, and markets) are directly related to residents' quality of life and the level of social development. A higher density of service facilities enhances residents' convenience, improves social welfare, and fosters community cohesion and development. Therefore, rural residential land use planning typically prioritizes the rational allocation of service facilities to meet the basic needs of residents. In contrast to urban areas, economic activities in rural regions are more reliant on agricultural production and primary processing than on industry or services, which results in a lesser impact of GDP and commercial facilities on rural residential land expansion. However, this dynamic may change as urban-rural integration progresses.

Overall, the impacts of various drivers on the expansion of different land use types in the three northeastern provinces vary significantly. A comprehensive analysis of all influencing factors is essential to provide informed recommendations for regional planning and strategic development.

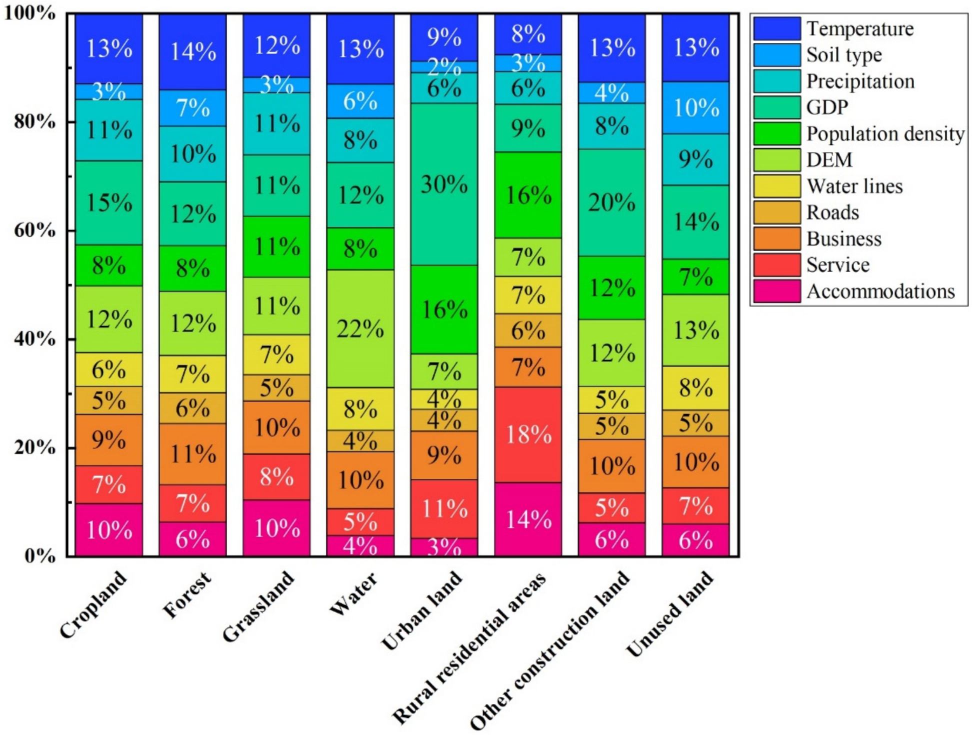


Figure 5. Contributions of each influencing factor

5.3 Potential Atlas of Land Expansion

Figure 6 illustrates the expansion probabilities of the eight land use types across the three northeastern provinces. Among these, cropland, forest, and grassland exhibit the greatest development potential and are suitable for cultivation across a wide range of areas. This indicates the potential for further synergistic development of agriculture, animal husbandry, and forestry, providing momentum for regional construction [57]. Cultivated land is expected to continue expanding in the plains, while also extending into the Sanjiang Plain in the northeast. Special attention should be given to the protection and management of the ecological environment during this expansion.

Woodlands are expanding steadily in the three major peripheral mountainous regions—Daxinganling, Xiaoxinganling, and Changbai Mountains—with the highest probability of expansion observed in the northernmost part of Heilongjiang. The northern regions of these provinces also offer favorable conditions for grassland expansion, which is likely to occur in these locations in the future. This potential for expansion is attributed to the favorable environmental conditions, including a suitable climate, abundant water resources, and fertile soils that promote vegetation growth.

Water bodies are most likely to expand in swamps, low-lying plains, estuarine zones, and along the coast of the Bohai Sea, particularly in the Sanjiang Plain. In line with the policy of returning farmland to forest and grassland, water bodies have also been nourished and protected, contributing to their gradual expansion.

Shenyang, Changchun, Harbin, and other provincial capitals have a high level of economic development and a well-established road transportation network. The central areas of these cities are suitable for town land expansion, with various types of construction land interspersed throughout. Dalian, Jilin, Qiqihar, and other major neighboring cities serve as key nodes for town expansion. In the future, the three northeastern provinces are expected to form a pattern of urban land expansion centered on large cities, radiating outward in concentric circles [58].

Rural residential land is particularly suitable for widespread distribution in the central plains, especially in areas with a warm climate. It has significant development potential in most parts of Liaoning Province, particularly in coastal areas. Beyond the central cities, the southern, central, and northeastern regions of the three northeastern provinces are also favorable areas for rural settlement land expansion. Dispersing the population and urban functions of central cities in these areas is a feasible strategy to alleviate the pressure on urban areas and promote balanced regional development. Additionally, other construction land is primarily linked to the expansion of urban and rural settlement areas, with limited potential for expansion in middle and high-latitude regions.

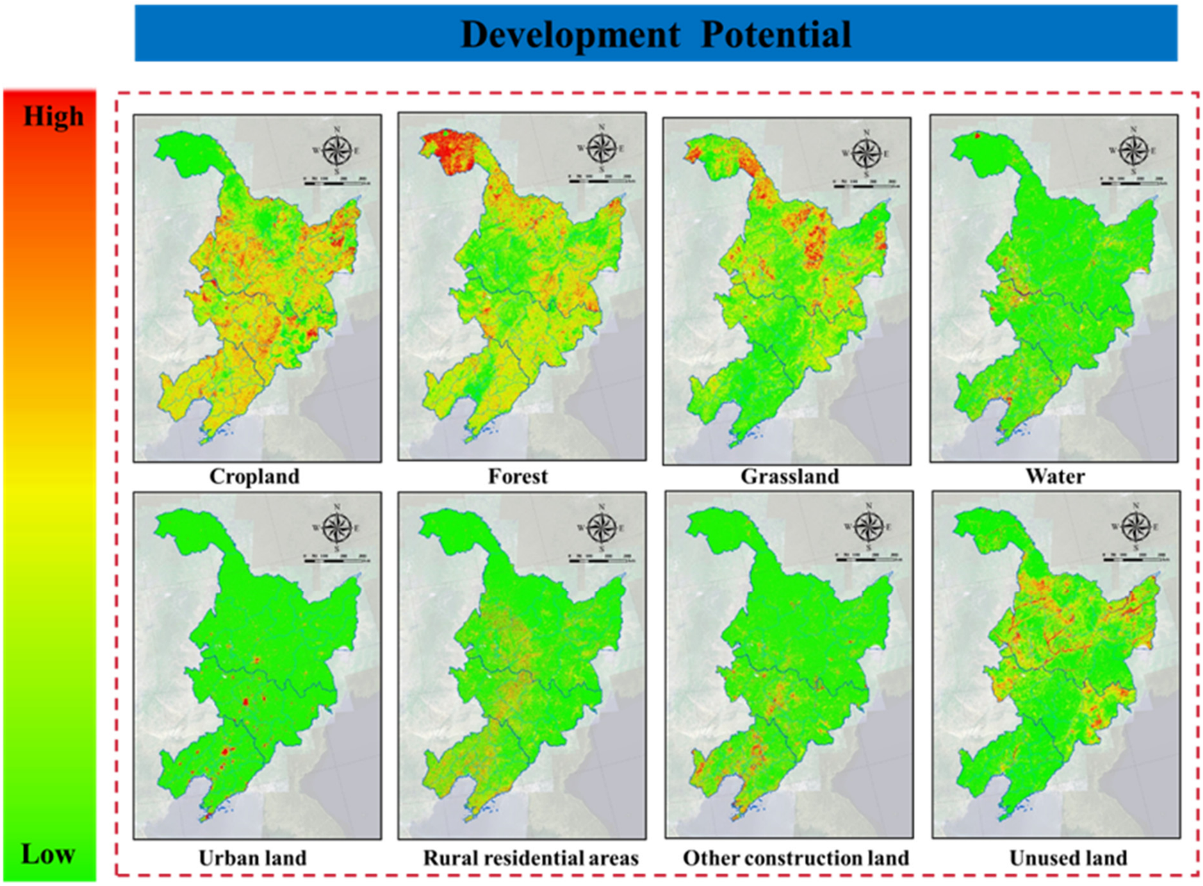


Figure 6. The potential for land-use expansion

5.4 Possibilities of Land-use Conversation

According to the Markov transition matrix, as shown in Figure 7, there are significant differences in the likelihood of conversion between different land use types in the three northeastern provinces. Cultivated land and forest land generally exhibit minimal changes, with less than 10% of these lands likely to undergo conversion. In contrast, the conversion rate of grassland is as high as approximately 50%, while the dynamic change possibilities for other construction land and unutilized land are also relatively high. Notably, more than half of the other construction land is prone to conversion, with about 26.4% potentially transforming into water bodies, reflecting a significant policy-driven protection effect. Urban and rural residential land are expected to remain relatively stable, with only about 20% likely to change. However, due to accelerated urbanization and a growing population in the major urban areas, urban land is gradually shifting towards rural residential land to alleviate the pressures associated with rapid urban expansion.

It is important to note that both grasslands and water bodies have a higher likelihood of conversion to unutilized land, with probabilities reaching around 10% and 20%, respectively. Unreasonable human activities, such as over-cultivation, improper livestock management, and sewage discharge, are the primary influencing factors. Conversely, the probability of conversion of arable land and forests to other land uses is lower and more stable. Furthermore, all land use types, except forests, show a tendency to be converted to cropland. This highlights the critical role of agricultural food production in the Northeast and the growing national demand for food.

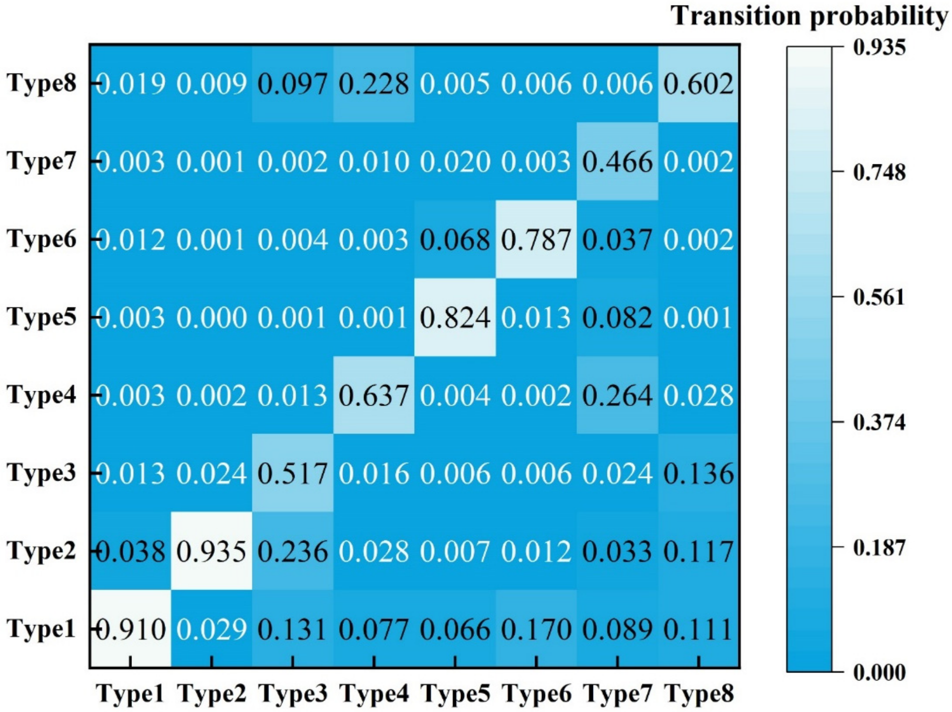


Figure 7. Markov matrix. T1: Cropland, T2: Forest, T3: Grassland, T4: Water, T5: Urban land, T6: Rural residential areas, T7: Other construction land, T8: Unused land

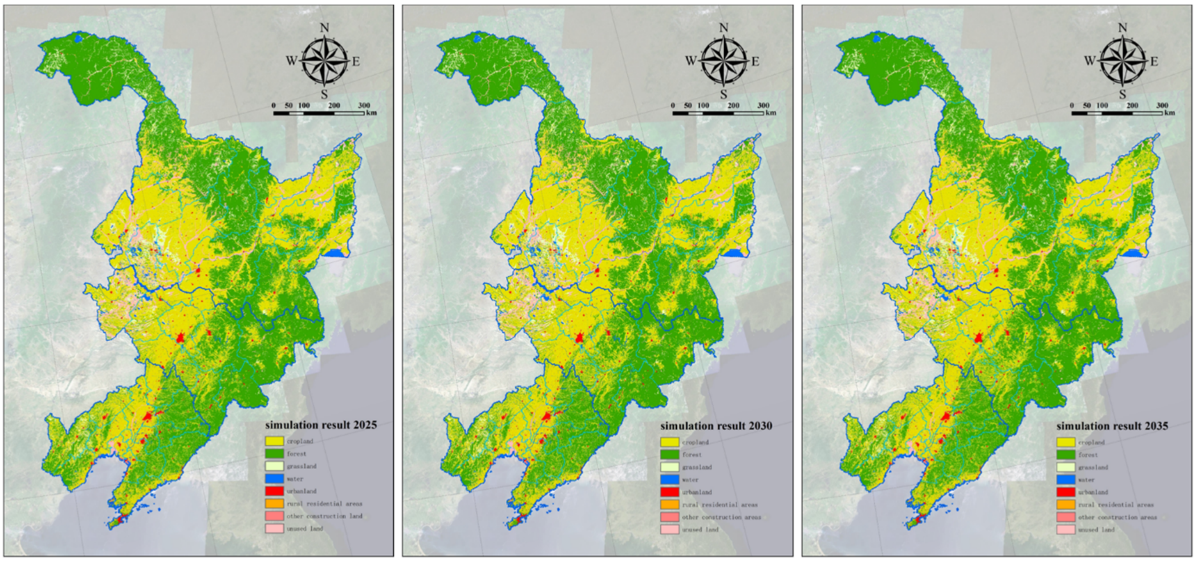
5.5 Results of Land Use Change Simulation

Figures 8 and 9 present the results of the land use simulation for the three northeastern provinces. Over the next ten years, with the support of national policies, the project of returning farmland to forests is progressing well. The area of cultivated land is projected to decrease from 300,556.3 km² in 2015 to 298,592.47 km² in 2035. The impact in regions such as the Changbai Mountain Range, Xiaoxinganling Mountains, and other areas is particularly significant. In the next decade, the arable land in the Sanjiang Plain and Songnen Plain will decrease, with more farmland being converted into ecological land. Forests in the northern and eastern parts of Northeast China are expanding, and the forest area is expected to grow by 20,879.78 km² over these 20 years. In contrast, grasslands and water bodies are experiencing significant shrinkage due to irrational utilization.

In addition, with the acceleration of urbanization and population growth, cities of all sizes are in the process of expanding their built-up areas to foster development. Urban land is expected to increase by 1,580.76 km² from 2015 to 2020, with smaller cities emerging around the central provincial capitals, further increasing the level of urbanization. The associated areas of land for residential, commercial, and service facilities have also expanded. Meanwhile, urban sprawl has led to the expansion of rural residential land to accommodate shifting populations and growing marginal communities, thereby easing intra-urban conflicts.

Importantly, the projected decrease in the areas of unutilized land and cultivated land, alongside the significant increase in ecological areas, reflects the country's growing emphasis on environmental protection, ecological balance, and the sustainable development of land use. Given the triple demands of population, food, and environmental concerns, unutilized land is expected to undergo continuous development.

Over the past two decades, land use types have undergone relatively little dynamic change, with reduced frequency of inter-conversion between various land use types. The rate of urban expansion is anticipated to gradually slow down, particularly in large central cities. The predicted results of this study provide a useful reference for the high-quality, coordinated development of land in the three northeastern provinces.



a. Results of land use expansion in Three Northeast Provinces(2025)

b. Results of land use expansion in Three Northeast Provinces(2030)

c. Results of land use expansion in Three Northeast Provinces(2035)

Figure 8. Results of land use change simulation

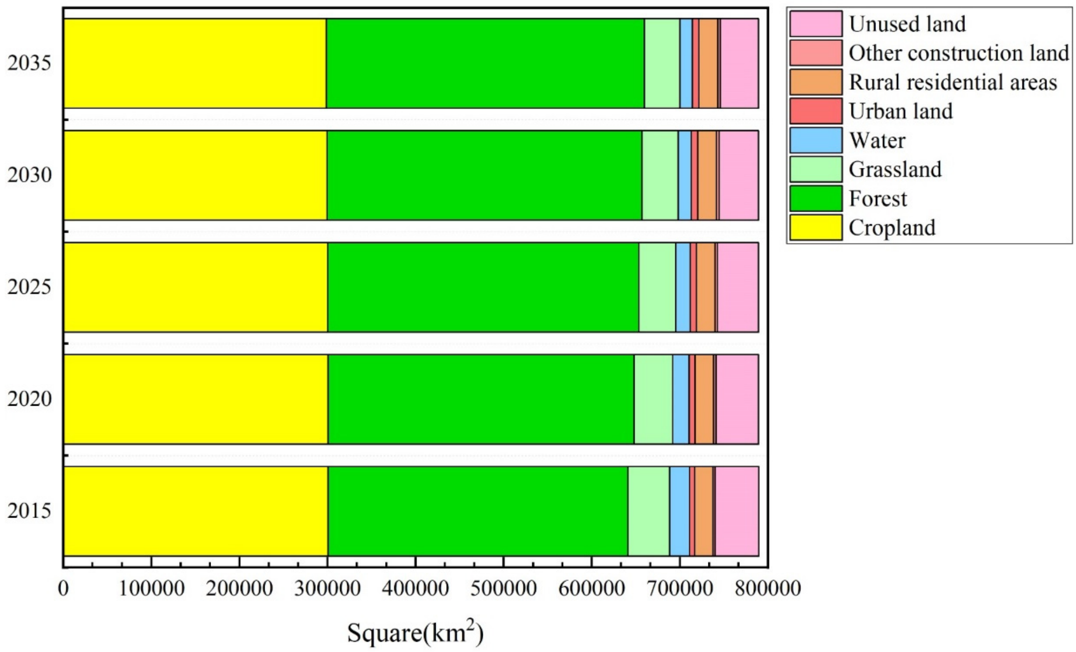


Figure 9. Area of land use types

Figure 10 presents the Sankey diagram illustrating land use shifts at different stages. Over the past decade (2015–2025), all land use types have experienced relatively significant transitions. The project of returning farmland to forests and grasslands has progressed well, with notable conversions of arable land into forests and grasslands, resulting in a net reduction in the area of cultivated land. Due to issues such as over-cultivation and land pollution, some arable land has been converted into unutilized land. Meanwhile, to ensure national food security, forest land, grassland, water bodies, rural residential land, and unutilized land have been redirected toward arable land. However, overall, the area of arable land remains insufficient to meet the demand. The total area transferred into forests, urban land, rural residential land, and other construction land exceeds the total area transferred from these land uses. The construction of protective forests has seen notable improvement, and with urban development and population growth, there has been a net increase in the area of urban and rural residential land, as well as other construction land, largely at the expense of arable land. Additionally, there has been a significant diversion of water bodies and grasslands, with grasslands being converted into cultivated land, forests, and unutilized land, resulting in a weakened capacity for soil and water conservation.

In the coming decade (2025–2035), the pace of land use change is expected to slow down. Cultivated land will continue to be converted into woodland and grassland, but at a significantly slower rate, thus effectively protecting cultivated land resources while achieving a win-win situation for ecological balance and food security. Unutilized land will continue to be developed and converted into forest land, grasslands, water bodies, etc., leading to an increase in "ecological green space" and a marked enhancement of ecosystem services. The urbanization process will stabilize, and the population's demands will drive the transfer of urban land and unused land to rural residential land, accelerating suburban urbanization. These shifts are likely to be driven by national policies, multiple drivers, and environmental protection strategies aimed at continuously adjusting and optimizing land use in the three northeastern provinces, to achieve comprehensive, coordinated, and sustainable development in the region.

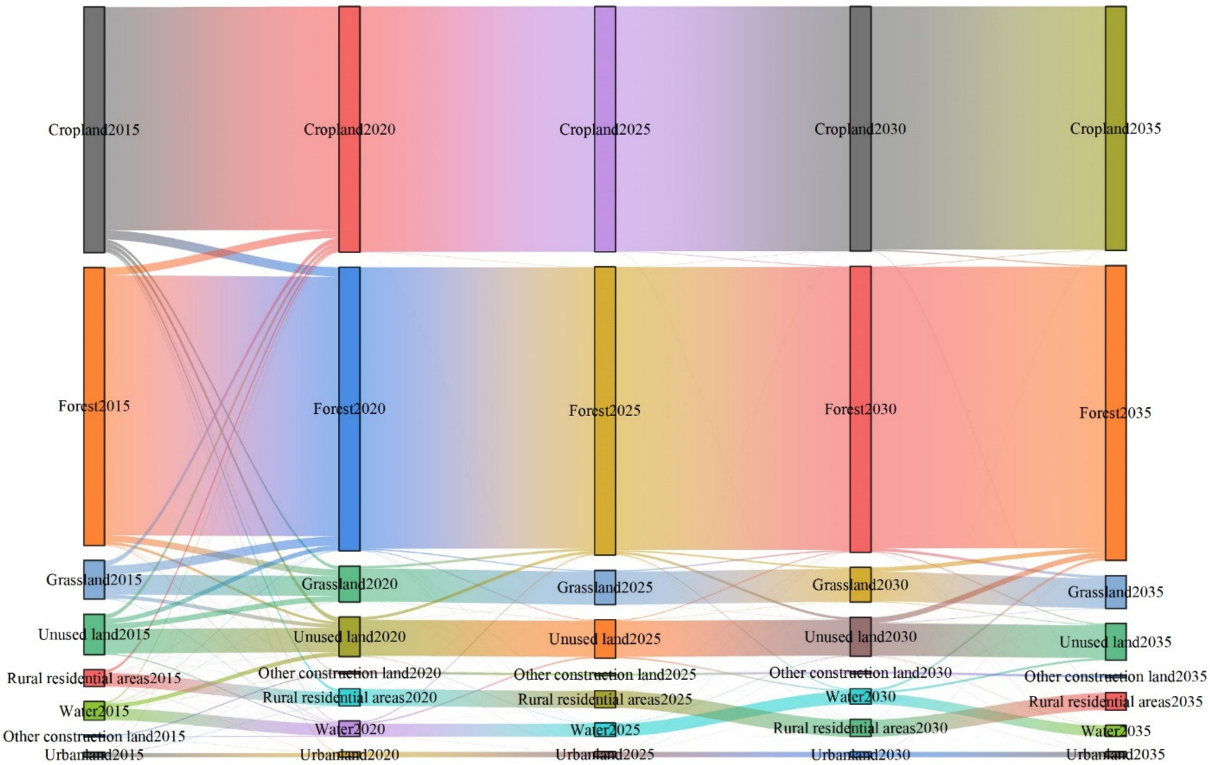


Figure 10. Land use transformation in Northeast China

6. Conclusion

This study uses the three northeastern provinces of China as a case study. By integrating land use data with various types of driving factor data, the following conclusions and contributions are drawn through the application of the PLUS model and Markov chain simulation to predict land use changes:

(1) **Analysis of land patch distribution**: By analyzing the land patch distribution in 2015 and 2020, the study reveals the expansion of each land use type over this period, with forest land and arable land showing the highest growth probabilities.

(2) **Validation of regional environmental factors**: Emphasis is placed on validating regional environmental factors (e.g., natural, economic, and social factor maps) to minimize discrepancies between the study's results and real-world observations. The LEAS model utilizes the random forest algorithm to assess the contribution of various drivers to land use change and to estimate the expansion probabilities for different land use types. The root mean square error (RMSE) of the simulations, as well as the out-of-sample RMSE, are used for model validation, improving its

interpretability and accuracy. Cultivated land, forests, and grasslands exhibit significant potential for development, reflecting the Northeast region's positive response to the national strategy for the synergistic development of agriculture, animal husbandry, and forestry. In contrast, urban land, rural residential land, and other construction land show a primarily linear development pattern, centered around the provincial capitals.

(3) **Markov chain analysis**: Using statistical data, the Markov chain model derived a transition matrix for land use types, revealing that the conversion probabilities for grassland, water bodies, other construction land, and developed land are approximately 50%. In comparison, the conversion probabilities for arable land and forests are much lower, around 10%, suggesting limited land use change in these areas. The CARS model integrates the Markov chain predictions by adjusting various parameters, continuously refining the simulated demand. This model predicts land use trends for 2025, 2030, and 2035, unveiling spatial evolution patterns that are significant for regional land use planning.

However, several limitations should be addressed in future studies: (1) The study covers a relatively short time frame, and its generalizability could be improved by extending the temporal scope. (2) The geographic data's low resolution may introduce errors during conversion, limiting the accuracy of the data and the generalizability of subsequent analyses. (3) The study does not account for the impact of nonlinear relationships or unexpected events on land use changes.

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