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Assessing the destabilization risk of ecosystems dominated by carbon sequestration based on interpretable machine learning method

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ABSTRACT

Increasing carbon sequestration (CS) in soils and biomass is an important land-based solution in mitigating global warming. Ecosystems provide a wide range of ecosystem services (ESs). The necessity to augment CS may engender alterations in the interrelationships among ESs, thereby heightening the probability of ecosystem destabilization. This study developed a framework that integrates machine learning and interpretable predictions to evaluate the destabilization risk resulting from alterations in ecosystem service relationships dominated by CS. We selected Northeastern China as study area to estimate six ESs and identified areas of destabilization risk among the three services most relevant to CS, including food production (FP), soil retention (SR), and habitat quality (HQ). Subsequently, we compared three machine learning models (random forest, extreme gradient boosting, and support vector machine) and introduced the Shapley additive interpretation (SHAP) method for driving mechanism analysis. The results showed that: (1) CS-FP had 30.28% of its area at destabilization risk and is the most significant ecosystem service pair; (2) Heilongjiang Province was the region with the highest destabilization risk of CS, with CS-FP and CS-SR accounting for 44.76% and 52.89% of all regions, respectively; (3) a non-linear relationship and the presence of threshold features between socio-ecological factors and the prediction of destabilization risk. The study has potential practical value for destabilization risks prevention, while also providing a scientific basis for formulating comprehensive carbon management policies and maintaining ecosystem stability.

1. Introduction

Since the industrial revolution, human activities, especially the overconsumption of fossil fuels, have resulted in a rising level of greenhouse gases (GHGs) in the atmosphere, triggering global climate change characterized by warming (Sun et al., 2022). This change poses a wide range of threats to the world in the areas of resources, energy, ecology and food security, which seriously challenges the survival and development of human beings (Zhao et al., 2022). In response to the challenge of global climate change, scientists and policymakers have proposed a variety of mitigation pathways to limit global warming to less than 1.5 °C. These pathways emphasize the need to rapidly increase the deployment of land-based solutions, including increased carbon sequestration in soil and biomass (Haughey et al., 2023; Smith, 2018). The provision of carbon sequestration (CS) by ecosystems to humans can mitigate greenhouse gas concentrations through the absorption and storage of atmospheric carbon dioxide, resulting in the formation of carbon sinks that facilitate above-ground vegetation growth and soil development, thereby promoting healthy ecosystem maintenance (Yin et al., 2023). Therefore, it is important to strengthen targeted research on carbon sequestration and to more fully understand its role and value in the ecosystem for achieving climate goals and promoting sustainable development.

However, ecosystems also provide a variety of other ecosystem services such as food production (FP), soil retention (SR) etc. Widespread research has demonstrated that there is a strong link between carbon sequestration and other ESs (Gao and Bian, 2019; Wang et al., 2024c;). Increasing the demand for CS may place additional burdens on

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ecosystems, leading to changes in the relationship between carbon sequestration and other ecosystem services. Ecosystem service relationships usually include trade-offs and synergies (Feng et al., 2021). Trade-off refers to the state of adversarial relationships between ecosystem services, while synergy refers to their cooperation and mutual reinforcement (Xue et al., 2023). When the probability of transitioning from a synergy to a trade-off relationship between CS and other ESs increases, it indicates that the stability of the ecosystem is being challenged and the capacity to restore equilibrium is weakened, thereby intensifying system dynamics and unpredictability (Spyra et al., 2020). This process of loss or reduction of equilibrium capacity is known as destabilization, and the resulting threat is called the destabilization risk (Fernández-Martínez et al., 2023). Despite the considerable attention devoted to ecological risks, prevailing studies have predominantly assessed and analyzed the complete spectrum of potential threats to ecosystems (Gong et al., 2021; Li et al., 2023), and there is a lack of targeted research on destabilizing risks. In addition, most studies have taken the loss of ecosystem services as a representation of risk in the risk assessment process, lacking attention to the dynamics and uncertainty of changes in ecosystem service relationships. Therefore, future studies should pay more attention to the dynamic interactions of ecosystem service relationships and their impacts on system stability. This will provide a more comprehensive framework for risk assessment and management and facilitate the effective management of the global carbon cycle.

The process of risk prediction follows the identification of risks, aiming to enhance comprehension and management of potential threats, as well as implement early preventive measures for mitigating damages caused by such risks. Machine learning (ML) models are effective for risk prediction problems and have been used in various fields including medicine, ecology and biology, such as disease prediction (Ali et al., 2021; Kavitha et al., 2022; Khan et al., 2023), accident detection (Adewopo et al., 2023; Ahmed et al., 2023), ecological risk (Qiu et al., 2023; Zhang et al., 2023a) and geologic hazards (Youssef et al., 2023; Zhang et al., 2023b). However, ML are often considered "black box" models (Mangalathu et al., 2020). This means that it is difficult to interpret hidden biases in the data or identify weaknesses in the model without fully understanding the process of model output (Prendin et al., 2023). That is, in risk prediction, it is not clear why certain predictions need to be made or how specific features will affect the predictions. So, the lack of interpretability has so far limited the further use of more powerful ML approaches in risk decision support. As machine learning continues to evolve, interpretable machine learning methods have emerged. The goal of interpretable machine learning is to understand how models make predictions and answer questions, such as the relationship between inputs and outputs, and which features are most important for predictions (Li, 2022). The Shapley additive explanations (SHAP) is a useful interpretability tool that can be added to machine learning works (Li et al., 2020a), which not only handles local and global explanations but also identifies whether the contribution of each input feature is positive or negative (Mangalathu et al., 2020). Currently, many ML models can be well integrated with SHAP, among which extreme gradient boosting (XGBoost), light gradient boosting machine (LightGBM), random forest (RF) and support vector machine (SVM) are more common. They are widely applied in pollution treatment (Wang et al., 2022a), energy fuels (Sharma Timilsina et al., 2024), carbon emissions (Luo et al., 2024) and disease occurrence (Lai et al., 2022; Liu et al., 2022b). However, relatively few studies have applied it to the destabilization risk of ecosystems. The application of interpretable machine learning methods to risk prediction can both utilize the powerful data processing and risk identification functions of machine learning and improve the transparency and effectiveness of prognosis interpretation and enhance risk management capabilities.

Northeastern China (NEC) is characterized by the largest continuous area of forested land in the country, extensive wetlands distributed throughout China, and is one of three black soil regions worldwide. The region is a crucial carbon sink and storage area and has a substantial capacity and rate for carbon sequestration (Cai et al., 2022; Yin et al., 2022; Zhang and Deng, 2022). CS has the risk of decreasing under the double pressure of natural and anthropogenic activities. Lu et al. (2021) found that wetland carbon pools in NEC decreased by 55–56 % from the 1980 s to the 2010 s. Long-term irrational farming and agricultural management practices have led to a decline in natural fertility, soil structure deterioration of black soils, and a decrease in soil organic carbon (Zhou et al., 2020). At the same time, the implementation of major ecological projects, such as the natural forest conservation and the grain to green, has a positive effect on stabilizing the carbon sequestration capacity of forests in the NEC (Lu et al., 2018; Mao et al., 2019). This coexistence of risks and opportunities leads to complex and variable relationships between carbon sequestration and other ESs. Therefore, it is necessary to conduct research on the CS of the NEC. By comprehending the interplay between CS and multiple ES, elucidating potential destabilization risks and system vulnerability, and discerning the underlying driving mechanisms behind these risks. This will not only facilitate the management of the dual pressure on CS arising from natural and anthropogenic activities, but also foster the sustainable development of NEC.

This study proposes a framework to assess the destabilization risk of changes in ecosystem service relationships based on the dominance of CS. First, we assessed six ESs of NEC, determined the ESs most closely related to CS, and revealed the relationships among them. Next, we identified the destabilization risks of CS and these ESs. Finally, we selected the optimal machine learning model for risk prediction and conducted a detailed explanatory analysis to explore the impact of socio-ecological features on destabilization risk prediction. The objectives of this study were to: (1) identify areas at risk of destabilization for CS, (2) employ machine learning techniques to enhance the accuracy of risk prediction, and (3) analyze significant features and threshold effects that influence the prediction of destabilization risk for CS and other ESs in order to optimize opportunities for risk intervention. The framework helps to better understand the complex relationship between carbon sequestration and other ecosystem services, identifies and prevents the destabilization risks arising from changes in the demand for ecosystem services, and provides an effective means of scientific carbon management, which is of great significance for addressing climate change and achieving sustainable development.

2. Materials and methods

2.1. Study area

The distribution administrative of NEC includes the four eastern leagues of the Inner Mongolia Autonomous Region (Chifeng, Tongliao, Hulunbeier City, and Xing'an League), Liaoning, Jilin, and Heilongjiang Province (38°42′N–53°35′N, 115°32′E–135°09′E), with a land area of approximately 1.24×10^6 km^2 (Fig. 1). Most of the study area has a temperate continental monsoon climate characterized by cold winters and cool summers, with significant variations in temperature throughout the year. The average annual precipitation over many years ranges from 250 to 1000 mm (Xiang et al., 2022). The vegetation type is dominated by deciduous broad-leaved and coniferous forests, and the forest area is the largest in the country. As a result of the dramatic increase in demand and rapid socioeconomic development, the region has experienced major anthropogenic environmental changes such as deforestation, agricultural expansion, and urbanization, which have profoundly altered the landscape pattern and ecosystem functioning, exacerbating ecological risks such as soil erosion and vegetation degradation, and posing a major challenge to the sustainability of ecosystem services (Wang et al., 2022b).

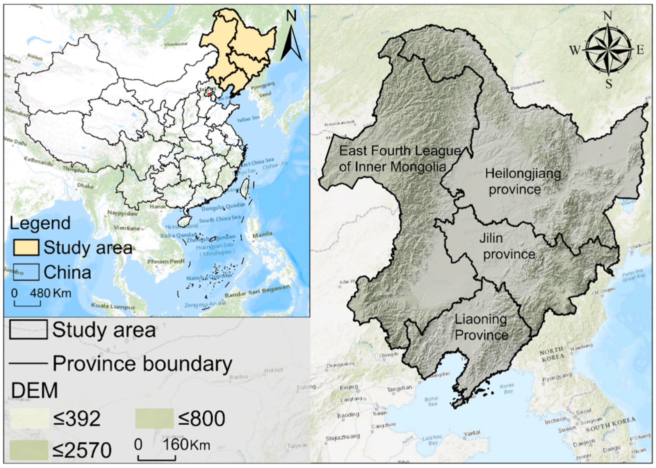

Fig. 1. Location of the study area.

2.2. Evaluation framework

The aim of this study was to assess the destabilization risk of the dynamic interplay between multiple ecosystem services dominated by carbon sequestration, to provide a basis for decision makers to develop effective climate management measures to realize sustainable development in the region. Fig. 2 illustrated the evaluation framework for this study, including the theoretical framework and specific analytical framework. Based on the loss and probability multiplication paradigm of risk assessment, our proposed theoretical framework is based on two dimensions – destabilization and probability. Destabilization is defined as the imbalance and degradation of ecosystem as manifested by a shift from synergies to trade-offs in ecosystem services. In addition to this, socio-ecological features are used as indicators of the risk probability. And across both the past and future time scales of ecosystems (Fig. 2). The analytical framework of this study, which consisted of the following three steps. First, we assessed six ecosystem services using the InVEST model and the quantitative indicator assessment approach and performed correlation analyses at multiple spatial scales to identify the three services most relevant to carbon sequestration, including food

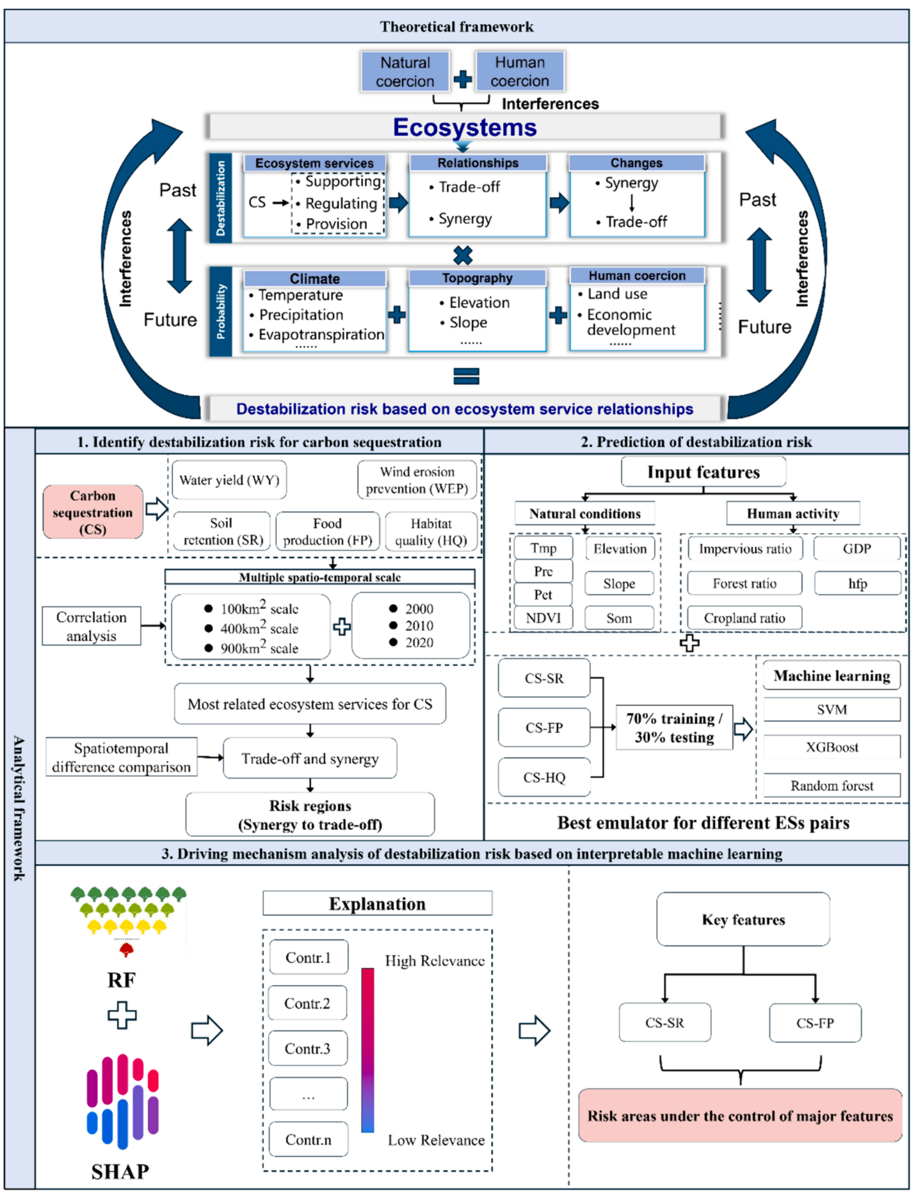

Fig. 2. Framework for destabilization risk assessment based on ecosystem service relationships.

production (FP), soil retention (SR), and habitat quality (HQ). We also determined the trade-offs and synergies between them and identified areas at destabilization risk. Then, we used three machine learning models (random forest, extreme gradient boosting, and support vector machine) and selected 12 socio-ecological variables as input features for machine learning to determine the best model for destabilization risk prediction. Finally, we conducted a detailed interpretive analysis of the risk prediction results based on the optimal machine learning model and the SHAP interpretable method to explore the impact of socio-ecological characteristics on destabilization risk prediction.

2.3. Data and processing

Multisource datasets were used to evaluate the ESs and important factors (Table 1). All the raster data with different spatial resolutions were resampled to a consistent spatial resolution of 1 km × 1 km.

2.4. Identification of destabilization risks

2.4.1. Ecosystem services assessment

Based on previous studies, we first quantitatively estimated six ecosystem services that are common in the study area (carbon sequestration, soil retention, food production, habitat quality, water yield, and wind erosion prevention services) (Wang et al., 2024b; Xiang et al., 2022). Three types of services that maintained a significant effect on CS were selected based on the results of the correlation analysis among the ecosystem services: food production (FP), soil retention (SR), and habitat quality (HQ) (Table 2). The specific estimation methods, parameters, results of correlation analysis and precision tests of ESs used in this study are presented in the supplementary material (Table A1-A3 and Fig. A1-A4).

2.4.2. Quantification of trade-off/synergy between ecosystem services

Differences in spatial scales affect the quantification of the relationships between ecosystem services. Therefore, we extracted ecosystem service values at 10 km × 10 km, 20 km × 20 km, and 30 km × 30 km pixel scales using the “zonal statistics” in ESRI ArcGIS software

Table 1
Description of data used in the study.

Data used	Data format	Spatial resolution
Land use	Raster (30 m × 30 m)	Earth System Science Data (https://essd.copernicus.org/articles/13/3907/2021/)
Meteorological data	Raster (1 km × 1 km)	National Tibetan Plateau Science Data Center (https://data.tpdc.ac.cn)
Soil organic matter (Som)	Raster (1 km × 1 km)	National Tibetan Plateau Science Data Center (precipitation, temperature, and evapotranspiration dataset) (https://data.tpdc.ac.cn)
NDVI	Raster (250 m × 250 m)	MOD13Q1 (https://modis.gsfc.nasa.gov/)
Net Primary Productivity (NPP)	Raster (500 m × 500 m)	MOD17A3(https://modis.gsfc.nasa.gov/)
Digital Elevation Model (DEM)	Raster (30 m × 30 m)	National Geospatial Data Cloud (https://www.gscloud.cn/)
Gross Domestic Product (GDP)	Raster (1 km × 1 km)	China’s GDP at the pixel level by nighttime lights time series and population images based on Zhao et al. (2017)
Human footprint (hfp)	Raster (1 km × 1 km)	An index compounded by different human pressures (built environments, croplands, population density, nightlights, railways, major roadways, and navigable waterways) based on Mu et al.(2022)
Slope	Raster (30 m × 30 m)	Obtained based on ArcGIS slope analysis tool
Socio-economic data	Tabular format	Statistical yearbooks and statistical bulletin of national economic and social development, including meat and food production, etc.

version 10.8. Before correlation analysis, the variables were standardized to eliminate size differences between the variables. Correlation analysis was performed using R software version 4.3.2 with the “corrplot” package. The spatiotemporal difference comparison method was applied to determine the trade-off/synergy relationships among ESs over a specific period (Zhao and Li, 2022). As ecosystem services were significantly correlated at all spatial scales, subsequent studies were quantified at a pixel scale of 20 km × 20 km to ensure a moderate number of cells. Correlation analyses were performed for all spatial scales in the supplementary material (Fig. A2-A4). The details of the different comparison methods were as follows.

The synergy/trade-off degree (TSD) was calculated with Equation (1). If the value of TSD was greater than 0 (zero), there was a synergy. Otherwise, it indicated the existence of a trade-off relationship, and the absolute value indicated the magnitude of the relationship between the two ecosystem services.

$$TSD = \begin{cases} 0 & (ES_{i,t_2-t_1} \times ES_{j,t_2-t_1} = 0) \\ \sqrt{\left(\left(ES_{i,t_2-t_1}\right)^2 + \left(ES_{j,t_2-t_1}\right)^2\right)/2} & (ES_{i,t_2-t_1} \times ES_{j,t_2-t_1} > 0) \\ -\sqrt{\left(\left(ES_{i,t_2-t_1}\right)^2 + \left(ES_{j,t_2-t_1}\right)^2\right)/2} & (ES_{i,t_2-t_1} \times ES_{j,t_2-t_1} < 0) \end{cases} \quad (1)$$

where $ES_{i,\ t2-t1}$ and $ES_{j,\ t2-t1}$ are the relative changes in the ESs of the *ith* and *jth* type during the period t_2-t_1, respectively, and were calculated as follows:

$$\mathrm{ES}_{\mathrm{i},t_2\text{-}t_1} = \left(\mathrm{ES}_{\mathrm{i},t_2}\text{-}\mathrm{ES}_{\mathrm{i},t_1}\right)/\mathrm{ES}_{\mathrm{i},t_1} \quad (2)$$

$$\mathrm{ES}_{\mathrm{j},t_2\text{-}t_1} = \left(\mathrm{ES}_{\mathrm{j},t_2}\text{-}\mathrm{ES}_{\mathrm{j},t_1}\right)/\mathrm{ES}_{\mathrm{j},t_1} \quad (3)$$

After identifying relationships between CS and other ecosystem services, we defined areas where synergies shifted into trade-offs as destabilization risk areas and used them as risk sample data for subsequent risk prediction analyses.

2.5. Prediction of destabilization risks

The selection of models was critical for predicting the occurrence and progression of risk in the destabilization. We used R software version 4.3.2 and PyCharm software version 2021.3.3 to build three machine learning models: XGBoost, RF and SVM. The XGBoost was optimized distributed gradient boosting algorithms. It can effectively explore the nonlinear relationship between the dependent variable and each independent variable, while maintaining high prediction accuracy and calculating and ranking the relative importance of the predictor variables (Liu et al., 2024; Zhang et al., 2019). The RF was one of the widely used multi-class tree algorithms, which combined a decision tree through majority voting and ultimately exhibits high accuracy on different datasets and fast independent characteristics of learning (Breiman, 2001). It performed well in handling nonlinear and unbalanced data with good generalization and noise immunity (Fan et al., 2024; Wang et al., 2024a).The SVM was a popular machine learning algorithm that projects the input data by mapping a kernel function to a higher dimensional feature space that was easier to classify than the original feature space (Burges, 1998). Our research was dedicated to the problem of classification of data with unbalanced and multidimensional characteristics. In addition, many studies had shown that there was not a simple linear relationship between socio-ecological characteristics and risk occurrence (Guo et al., 2024; Li et al., 2023). Therefore, these three models, with their respective strengths and characteristics, accommodated different data characteristics and met the needs of this study. Moreover, they were often combined with SHAP and were widely used in studies (Lai et al., 2022). However, the differences in data sets can lead to variability in the performance capabilities of the three models. Therefore, in the risk prediction process, we compared the three models to determine the model with the best performance capability. In this

Table 2
Overview of ESs assessed in this study.

Ecosystem service type	Abbreviation	Description	Unit	Methodology
carbon sequestration	CS	Amount of carbon sequestered by terrestrial ecosystems	t	InVEST model
Soil retention	SR	Amount of soil retained by ecosystems	t	InVEST model
Habitat quality	HQ	Availability of suitable habitats for individuals and populations	/	InVEST model
Food production	FP	The yield of grain crop, meat production and aquaculture production	t	$FP_n = \sum_{i=1}^{i} A_{ni} \times P_{ni}$ Where FP_n denotes the production of farmland, grassland, and water area respectively (t); A_{ni} denotes the area of the n land-use types in the raster cell, respectively (km^2); P_{ni} denotes the yield per unit area of the main product (t/km^2).

study, the classification of trade-off/synergy shifts in ESs for 2000–2010 and 2010–2020 was considered as the response variable (synergy shifted to trade-off as 1 and trade-off shifted to synergy as 0), and socio-ecological factors, including 12 factors, namely, temperature (Tmp), precipitation (Pre), potential evapotranspiration (Pet), elevation, slope, soil organic matter (Som), normalized difference vegetation index (NDVI), forest cover, cropland cover, impervious surface cover, human footprint (hfp), and gross domestic product (GDP), were chosen as explanatory variables. All samples were randomly divided into training (70 %) and validation (30 %) sets. The predictive performance of these machine learning models was evaluated using accuracy, kappa, recall value, precision, F1, and the area under the receiver operating characteristic curve (AUC). Furthermore, a grid search approach was used to tune the hyperparameters of the three models. The grid search used an algorithm to specify several combinations of hyperparameters, used cross-validation to compute the model for each combination, and proposed the best combination with the highest training accuracy (Iban and Sekertekin, 2022). The results of the optimization and comparison of the machine learning models in this study are presented in the supplementary material (Table A4 and Fig. A5).

2.6. Driving mechanism analysis of destabilization risks

Understanding the mechanisms driving, including the important features and threshold effects that influence the prediction of destabilization risk, is essential for risk prevention and risk management in advance. For this reason, the interpretability of the model was considered key. Model interpretability is the process of understanding how a machine learning model makes its predictions by examining the relationships it has learned between input factors and outputs. Shapley additive explanations (SHAP) based on shape values from game theory can provide good explanations for both local and global models (Mangalathu et al., 2020). In this study, SHAP importance assessments were used to interpret the models globally, revealing which features play a key role in destabilization risk prediction. In addition to this, we used ten-fold cross validation for recursive feature elimination to filter the optimal number of variables (Fig. A6). Although the characteristic importance map depicted the input features that had the greatest impact on the destabilization risk, we could not elucidate how the input features affected this change. Thus, we used the SHAP dependency analysis to describe how a single feature influenced the outcome of the predictive model.

3. Results

3.1. Spatio-temporal distribution of destabilization risk areas

The largest areas that maintained an unchanged trade-off relationship between CS-SR and CS-FP from 2000 to 2010 to 2010–2020 were 35.31×10^4 km^2 and 46.39×10^4 km^2, respectively. The area of CS-HQ that maintained unchanged synergy was the largest at 70.49×10^4 km^2. This was followed by the area of synergy to trade-off, which was 33.85×10^4 km^2, 37.68×10^4 km^2 and 23.67×10^4 km^2 for CS-SR, CS-FP and CS-HQ, respectively (Fig. 3b). In terms of different administrative regions, CS-SR and CS-FP had the highest proportion of synergy shifting to trade-off in Heilongjiang Province, with CS-SR accounting for 52.89 %, and CS-FP accounting for 44.76 %. In CS-HQ, the four eastern leagues of Inner Mongolia exhibited the highest proportions of synergy shifting to trade-off, accounting for 50.09 % of the total (Fig. 3a and 3c).

3.2. Identification of importance features for destabilization risk prediction

Potential evapotranspiration, temperature, precipitation, and elevation were significant factors affecting the destabilization risk of ecosystem service in the CS-SR, and potential evapotranspiration, temperature, precipitation, cropland cover, NDVI and forest cover in the CS-FP (Fig. 4a). The predicted outputs of potential evapotranspiration, temperature, and elevation in the CS-SR were negatively influenced, whereas precipitation was positively influenced (Fig. 4b). The predicted outputs of potential evapotranspiration, temperature, NDVI and cropland cover on the CS-FP were negatively influenced, whereas precipitation and forest cover were positively affected.

3.3. Threshold effects of importance features

Considering the relative importance of the independent variables and the stability of the model predictions, we combined different models and feature quantification methods to select several variables and explore the nonlinear relationship between the independent and dependent variables, as shown in Fig. 5. Based on the prediction model, SHAP values for characteristic variables exceeding zero in the SHAP dependence plot, represent an increase in the probability of destabilization risks. The higher the SHAP value of a variable, the more likely it is that destabilization risks will occur for CS-SR and CS-FP. Specifically, the probability of CS-SR and CS-FP destabilization risks increased with the growth of potential evapotranspiration when potential evapotranspiration was less than 800 mm. Their probability of destabilization risk increased when the temperature was less than 4 °C. The probability of the CS-FP destabilization risks increased with precipitation when the precipitation ranged from 500 to 800 mm. When the elevation ranged from 250 to 750 m, the CS-SR destabilization risks decreased with elevation. CS-FP was more likely to be at destabilization risk when cropland cover was less than 0.2, NDVI was between 0.7 and 0.85, and forest cover was more than 0.9. The remaining factors had a more diffuse effect on the CS-SR and CS-FP.

Precipitation was more dispersed in CS-SR, so the high-risk areas in CS-SR went into consideration of potential evapotranspiration, temperature, and elevation. In CS-FP, since the high-risk areas were less and more dispersed after considering six important factors at the same time, we only considered the three factors of climate (Fig. 6). These regions are primarily concentrated in the northern part of northeastern China, including Heilongjiang province and Hulunbeier city in the Inner Mongolia Autonomous Region.

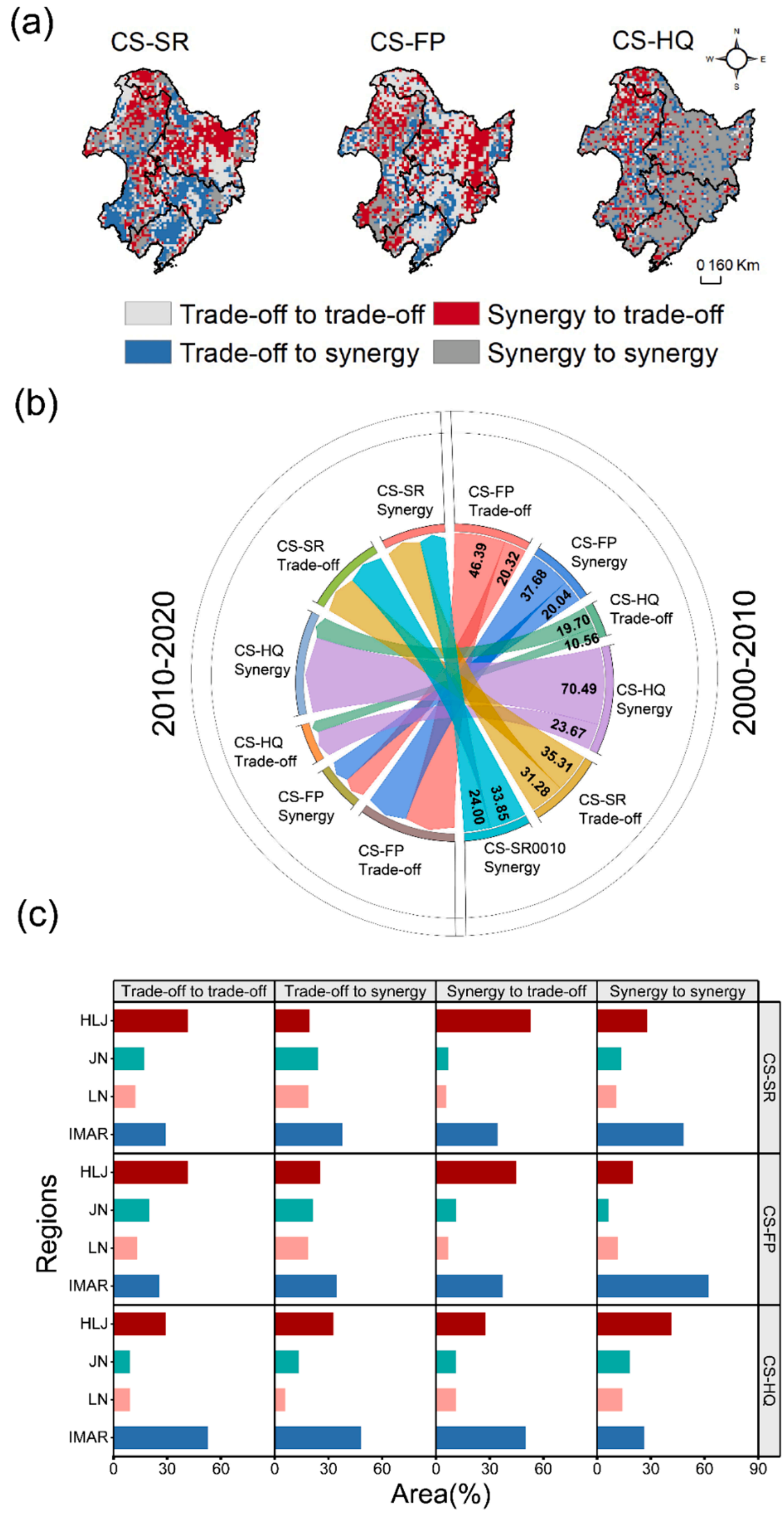

Fig. 3. Transfer of ecosystem service trade-off/synergy in the NEC. (a) Spatial distribution of trade-off/synergy shifts from 2000-2010 and 2010-2020. (b) Area of ecosystem service trade-off/synergy shift (× 104 km 2). (c) Area proportion of ecosystem service trade-off/synergy shift in different provinces (%). HLJ, LN, JL, and NMG in Heilongjiang, Liaoning, Jilin, and the four eastern leagues of the Inner Mongolia Autonomous Region, respectively.

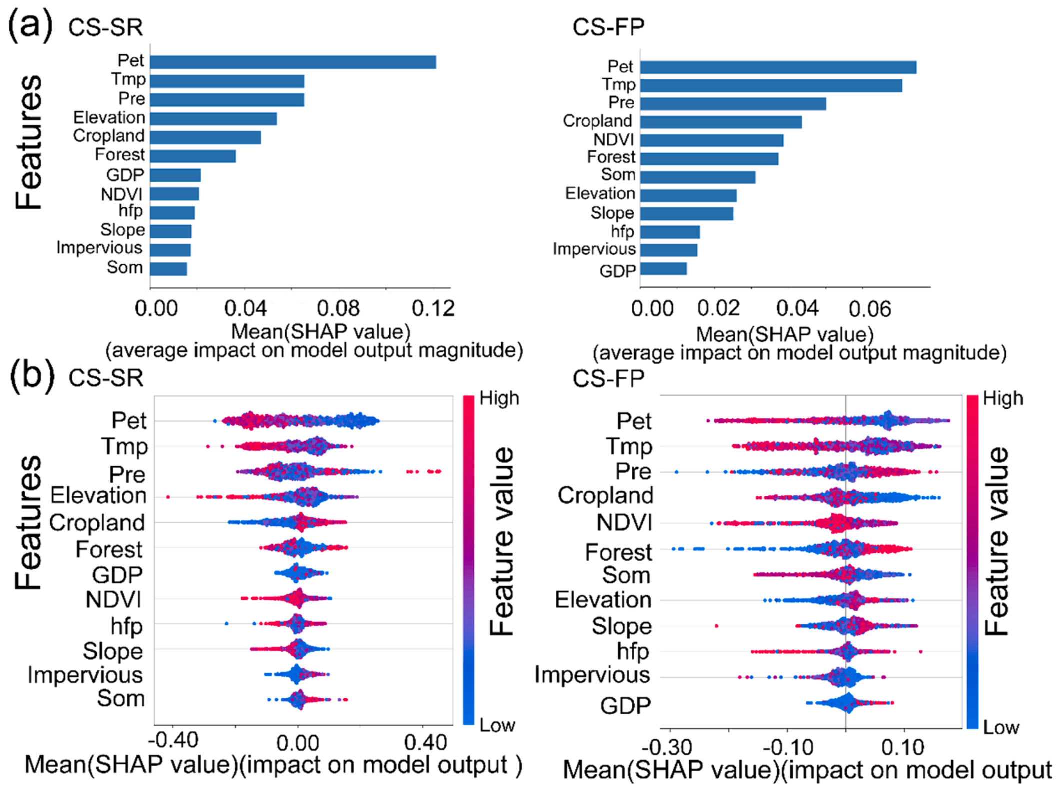

Fig. 4. Feature importance analysis using the SHAP method for the RF model. (a) Absolute importance scores, indicating the average impact of each factor on the on the classification. (b) SHAP summary plot. These values represent the local contribution of each factor in the destabilization risks prediction in training the model and are arranged in the order of their importance. The x-axis displays the SHAP values, while the y-axis displays the features. Each dot represents a sample from the input dataset, and the color of the dot indicates the value of the features. The horizontal position of the point indicates whether the features have a positive or negative effect on the prediction.

4. Discussion

4.1. Applicability of the framework for destabilization risk assessment

To enhance the assessment and management of destabilization risk, we established a framework for destabilization risk assessment that closely links human well-being to ecosystems, taking the ecosystem service relationship as the assessment endpoint. The utilization of this framework enables us to more effectively evaluate the risks associated with fluctuations in demand for a specific ecosystem service and implement strategic interventions to achieve a mutually beneficial outcome for all stakeholders. The framework's flexibility also enables it to function as a universal tool for evaluating the potential risk of destabilization associated with shifts in demand for specific ecosystem services across different regions.

To establish and validate a framework for assessing the risk of destabilization, we employ an interpretable machine learning approach. This approach can unveil the driving mechanisms influencing destabilization risk and facilitate our comprehension of the socio-ecological features that impact its occurrence, as well as elucidate their respective roles. Although many studies have demonstrated the prognostic capacity of socio-ecological features for ecological risk (Li et al., 2023; Xing et al., 2020), this study further identifies important features that affect the prediction of destabilization risk for CS-FP and CS-SR. By using SHAP values, we found that climate, land use, and topographic factors are important features that are essential to provide the best risk assessment. This is consistent with the results of previous studies(Dai and Wang, 2024; Wu et al., 2021; Zhang et al., 2020a; Zhao et al., 2023). We further validate the results of the SHAP analysis using other importance indicators at the same time, and the validation results show a high degree of consistency (see Supplementary Material Fig. A7 for details). Furthermore, it demonstrates that the ML approach can account for key characteristics and build a highly accurate predictive model of destabilization risk caused by socio-ecological factors. This finding provides an important reference for future risk management and decision-making. By understanding this destabilization, governments and researchers can take precautionary measures to both ensure a balance between CS and other ESs, and to better respond to climate change in the wake of increased CS demand. However, the risk prediction of CS-HQ shows not so excellent results in all machine learning. On the one hand there are fewer destabilizing risk regions between CS-HQ. On the other hand, the selected features may not be sufficient to fully characterize the target variables. Therefore, the study of destabilizing risk for CS-HQ needs to be further explored in depth.

4.2. Relevant tasks derived from risks linked to destabilization

The interactions among ESs have been widely acknowledged. In our study, we specifically focused on three ESs – soil retention, food production, and habitat quality – which are closely associated with carbon sequestration. We aimed to identify the trade-offs or synergies existing among these services. Previous studies also demonstrated a robust correlation between CS and these services (Huang et al., 2023; Li et al., 2020b; Qiao et al., 2019). The findings of our study unveil a significant area of potential destabilization risk in the NEC, where synergies transform trade-offs between carbon sequestration and crucial ecosystem services such as soil retention, food production, and habitat quality. The expansion of social development has led to modifications in the structure and function of ecosystems through human activities (Felipe-Lucia et al., 2020). This phenomenon disrupts not only the equilibrium among diverse ecosystems but also undermines their capacity to provide essential ecosystem services, thereby increasing the

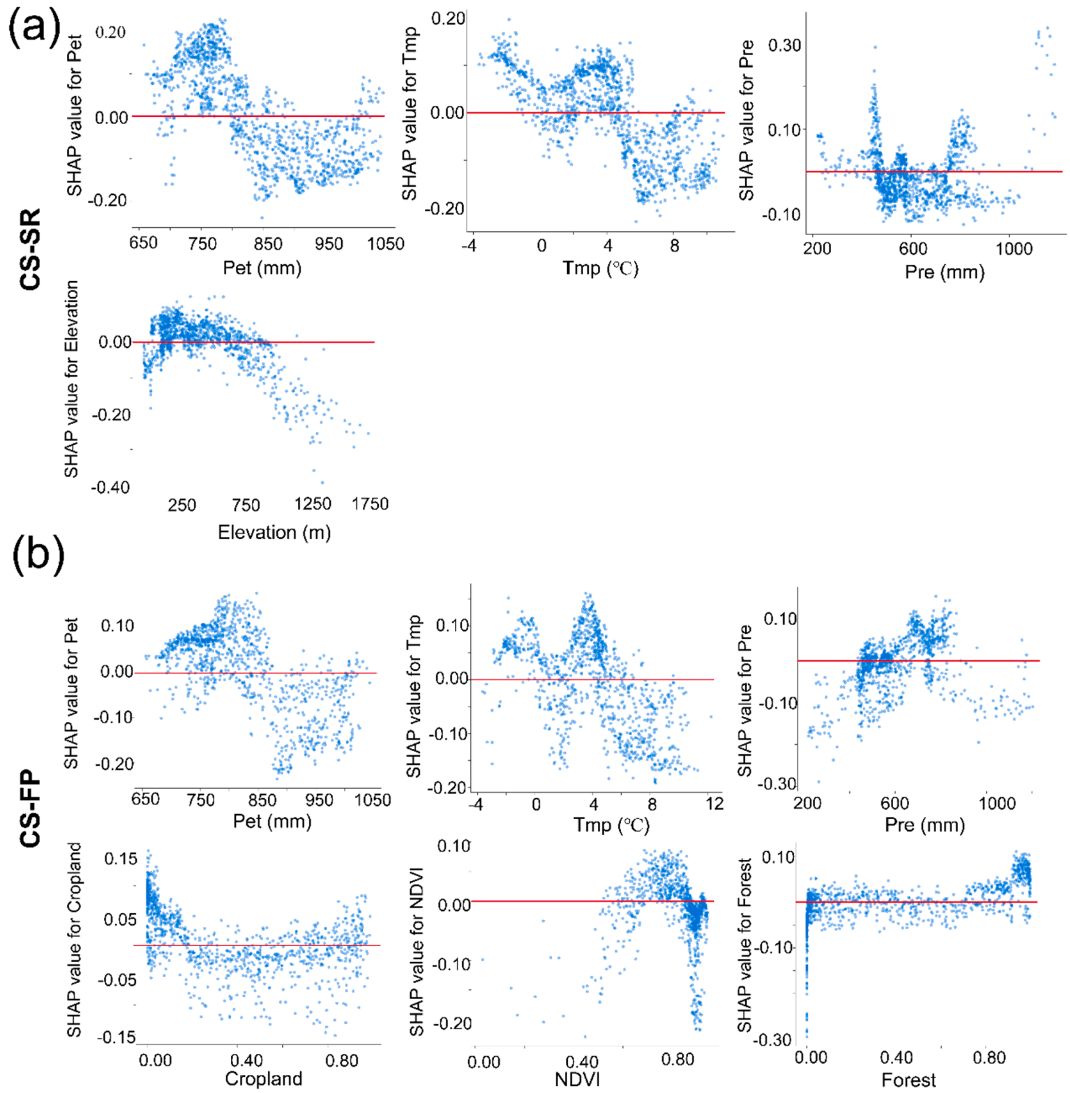

Fig. 5. SHAP dependence plot of the RF model. (a)The SHAP dependency plots of variables that rank higher in relative importance at RF results for CS-SR. (b) The SHAP dependency plots of variables that rank higher in relative importance at RF results for CS-FP. The SHAP dependence plots show how a variable's value impacts the prediction (y-axis) of every observation in the dataset.

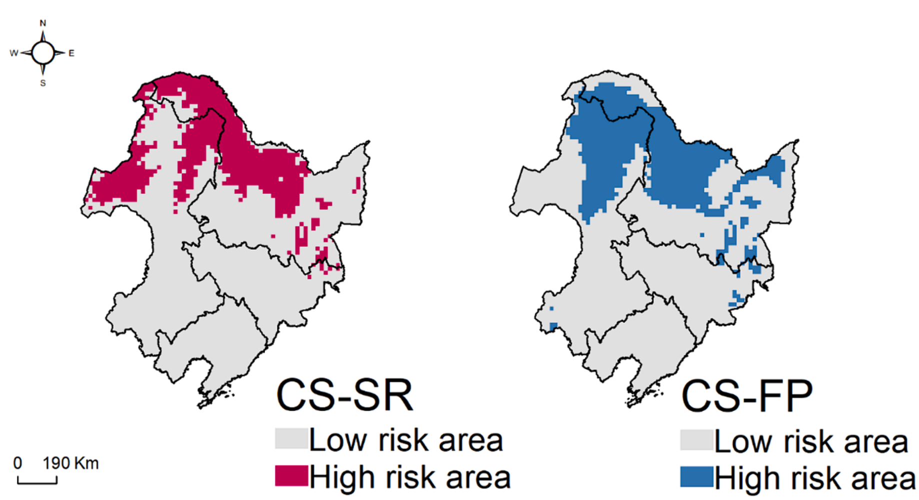

Fig. 6. Risk areas under the control of major factors. Risk areas extracted by CS-SR (Pet < 800 mm, Tmp < 4°C, 250 m < elevation ≤ 750 m). Risk areas extracted by CS-FP (Pet < 800 mm, Tmp< 4°C, 500 mm < Pre ≤ 800 mm).

likelihood of conflicts arising from competition for these services. The aforementioned transformations may lead to the emergence of increasingly intricate and irreversible ecosystems. Therefore, early identification of areas prone to destabilization and the implementation of appropriate management strategies are imperative in order to mitigate further degradation of ecosystems. The destabilization risk between carbon sequestration and food production is most pronounced in the NEC. This highlights the importance of addressing the trade-offs between increased demand for carbon storage and ensuring food production in response to climate change.

Heilongjiang Province is a typical high prevalence area of destabilization risk for CS-FP and CS-SR. This is particularly noticeable in major ecosystems such as farmland and forests. It accounts for more than half of the cultivated area in the typical black soil areas of the study area, and its grain production ranks first in the country (Tang et al., 2024). Compared with other provinces, Heilongjiang boasts a larger expanse of arable land, a more extensive distribution of fertile black soil, and heightened agricultural productivity. However, it also has more frequent agricultural activities (Lu et al., 2022). Agro-ecosystems are anthropogenic in nature, and the provision of agro-ecosystem services is a co-production between natural ecosystems and human activities (Zabala et al., 2021). The intricate nature of the agro-landscape itself, coupled with the frequent human interventions in land-use allocation and their preferences, engenders a trade-off between provisioning services provided by agro-ecosystems and other associated services (Aryal et al., 2022; Cao et al., 2020). In addition to this, this risk is not only closely related to land-use change but is also strongly influenced by changes in agricultural practices and management measures. For example, introducing new irrigation systems can significantly heighten the trade-off between carbon storage and soil conservation (Zhong et al., 2020). Therefore, prioritizing the adjustment of CS-FP and CS-SR trade-offs to address the destabilization risk is an important strategy for Heilongjiang Province to ensure long-term sustainable development. The government should devise policies that not only uphold its status as China's primary agricultural production hub, but also mitigate environmental impacts and bolster carbon sequestration and soil conservation capabilities through land use optimization and agricultural efficiency improvements, thereby fostering economically viable and ecologically sustainable development. In order to effectively achieve climate objectives, it is imperative to consider the potential risks of destabilization associated with carbon sequestration and embrace a comprehensive and well-balanced approach. This ensures that carbon storage strategies not only efficiently capture carbon but also uphold or enhance ecosystem stability.

4.3. *The critical role of threshold effects in early intervention for destabilizing risk*

To acquire a more profound comprehension of this intricate nonlinear association and the existence of thresholds, we conduct further analysis on the intricate interplay between socio-ecological characteristics and destabilizing risks. Crops and plants are frequently exposed to a combination of climatic stressors, which exert an impact on their growth and development, consequently influencing ecosystem services and relationships through the intricate interplay of multiple climatic variables (Zhang et al., 2020b). The findings of our study indicated an increased risk of destabilization for both CS-SR and CS-FP when potential evapotranspiration is below 800 mm, and the mean annual temperature was less than 4 °C. The destabilization risk for CS-FP was likely to increase as precipitation levels rose from 500 to 800 mm. The likelihood of destabilization risk for the CS-SR is heightened when the elevation ranged from 250 and 750 m. The distribution areas of these regions highly coincide with those of forests. Forests in the NEC region play a pivotal role as primary ecosystems, providing indispensable services such as carbon sequestration and soil retention. In the 21st century, NEC has undergone a series of structural and environmental landscape changes, with forest ecosystems exhibiting distinct temporal variations influenced by anthropogenic activities (e.g., deforestation, implementation of ecological restoration projects, and expansion of cropland) and climate change (Shi et al., 2017). This instability leads to the possibility of increased trade-offs in the services provided by ecosystems. For instance, most NEC regions have experienced a consistent warming trend since 1982 (Li et al., 2021; Liu et al., 2022a), with elevated temperatures enhancing photosynthesis via metabolic processes and augmenting nutrient availability through accelerated decomposition rates, thereby promoting CS. In 2020, precipitation increased in the northern region of NEC compared to previous years. Consequently, this increase results in localized soil erosion, which is not conducive to enhanced soil retention (Ran et al., 2020). The implementation of the Natural Forest Conservation Project (NFCP) and Grain to Green Project (GTGP) policies has resulted in an augmentation of vegetation cover, leading to enhanced evapotranspiration, reduced water yield, and increased soil retention (Mao et al., 2019; Wang et al., 2022b). However, an increase in vegetation cover results in a reduction in the local average temperature, which subsequently weakens photosynthesis and slows down decomposition rates. This phenomenon is not conducive to enhancing the CS (Cao et al., 2023; Massaro et al., 2023). Furthermore, the detrimental impacts on natural forests and the protracted and delayed processes of ecological restoration also contribute to a decline in carbon sequestration, posing challenges for short-term recovery (Yu et al., 2011). While natural factors play a pivotal role in influencing the risk, it is imperative to acknowledge the significant impacts of anthropogenic activities, particularly those associated with land-use change. Land-use change alters the structure and function of ecosystems and directly affects ecosystem services and their trade-offs (Zheng et al., 2022). For instance, the destabilization risk of CS-FP is enhanced in areas with less than 20 % cropland area. Forests are widely distributed throughout these regions. In NEC, cropland expansion shows a strong negative correlation with forest expansion (Shi et al., 2017). As forest coverage declines, there is a corresponding reduction in carbon sequestration, whereas food production increases. By understanding the key features that influence the prediction of destabilization risks, managers can better identify and prioritize areas for observation based on thresholds, thereby mitigating risk and increasing the likelihood of achieving synergies between carbon sequestration, food production and soil protection.

5. Conclusion

We identified three ESs (SR, HQ, and FP) that exhibited strong associations with carbon sequestration services in NEC and the trade-off/synergy among them, thereby elucidating the destabilization risk areas between them and CS. The destabilization risk prediction model was constructed using machine learning and SHAP methods, exploring the risk prediction mechanism and threshold effect, and providing a clear explanation for personalized risk prediction. Our findings demonstrate a discernible upward trajectory in the trade-off dynamics among SR, HQ, FP, and CS within the NEC region. It is particularly noteworthy that the destabilization risk between CS and FP is significant. The distribution of the trade-off between CS-SR and CS-FP is significant in Heilongjiang Province, which is also a major area of destabilizing risk. There are nonlinear and threshold effects between socio-ecological factors and destabilization risk. Among them, natural factors, especially climatic factors, have a greater impact than socio-economic factors. This study offers valuable insights for enhancing the management of ecosystem services, safeguarding carbon pools within ecosystems, and optimizing carbon sequestration to achieve the harmonious integration of social, economic, and environmental benefits. At the same time, it provides a positive methodological reference for the prediction and interpretation of destabilizing risk.

CRediT authorship contribution statement

Lingli Zuo: Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Data curation, Conceptualization. **Guohua Liu:** Visualization, Validation, Supervision, Conceptualization. **Zhou Fang:** Resources. **Junyan Zhao:** Data curation. **Jiajia Li:** Data curation. **Shuyuan Zheng:** Data curation. **Xukun Su:** Visualization, Validation, Supervision, Resources, Funding acquisition, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. . Supplementary data

The following are Supplementary data to this article:

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2024.112593.

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