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RESEARCH ON INFLUENCING FACTORS OF THE STABILITY OF ARABLE LAND PRODUCTION CAPACITY IN HEILONGJIANG PROVINCE

ИССЛЕДОВАНИЕ ФАКТОРОВ, ВЛИЯЮЩИХ НА СТАБИЛЬНОСТЬ ПРОИЗВОДСТВЕННОГО ПОТЕНЦИАЛА ПАХОТНЫХ ЗЕМЕЛЬ В ПРОВИНЦИИ ХЭЙЛУНЦЗЯН

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Abstract. Due to long-term intensive food production and unsustainable agricultural practices in some areas of China, cultivated land faces challenges such as soil depletion, reduced organic matter content, and deteriorating physical and chemical properties, which pose obstacles to the sustainable use of cultivated land and the steady increase in grain production capacity. The purpose of this study is to identify the main factors affecting the stability of arable land production capacity in Heilongjiang Province, to study their impact on the stability of production potential, and to develop a theoretical framework and practical recommendations for ensuring the quality development of regional agriculture and responding to fluctuations in global food prices. In this paper, Heilongjiang Province was selected as the research object, and data from 2001 to 2020 was used. The results showed that the stability of the production potential of arable land exhibited a significant upward trend in the east and a downward trend in the west of Heilongjiang Province. The impact of climate fluctuations and human activities on the stability of the production potential of arable land is characterized by significant spatial heterogeneity. There are obvious differences in the key factors and their direction of action in different regions. The stability of production capacity is largely influenced by climate fluctuations and human activities, and the effects of these two factors are significantly heterogeneous and generally weakening. In the future, it will still be necessary to pay more attention to analyzing changes in the stability of arable land production capacity in order to make effective land management decisions.

Аннотация. В связи с длительным интенсивным производством продовольствия и неразумными методами ведения сельского хозяйства в некоторых районах Китая обрабатываемые земли сталкиваются с такими проблемами, как истощение слоев чернозема, снижение содержания органических веществ в почве и ухудшение физических и химических свойств почвы, что создает проблемы для устойчивого использования обрабатываемых земель и стабильное увеличение мощностей по производству зерна. Целью данного исследования является выяснение основных факторов, влияющих на стабильность производственных мощностей пахотных земель в провинции Хэйлунцзян, изучение их влияния на стабильность производственного потенциала, а также развитие теоретического обоснования и разработка практических рекомендаций для обеспечения качественного развития регионального сельского хозяйства и реагирования на колебания цен на мировом продовольственном рынке. В данной статье в качестве объекта исследования выбрана провинция Хэйлунцзян, используются данные за период с 2001 по 2020 год. Результаты показали, что стабильность производственного потенциала пахотных земель продемонстрировала значительную тенденцию к росту на востоке и снижению на западе провинции Хэйлунцзян. Влияние колебаний климата и деятельности человека на стабильность производственного потенциала пахотных земель характеризуется значительной пространственной неоднородностью. Существуют очевидные различия в ключевых факторах и направлении их действия в разных регионах. Стабильность производственного потенциала в значительной степени зависит от колебаний климата и деятельности человека, и последствия этих двух факторов значительно неоднородны в пространстве и в основном ослабевают. В будущем по-прежнему необходимо уделять больше внимания анализу изменений стабильности производственного потенциала пахотных земель для принятия эффективных решений по управлению земельными ресурсами.

Keywords: Heilongjiang Province; China; production capacity; arable land; stability; influencing factors; protection of arable land

Ключевые слова: провинция Хэйлунцзян; Китай; производственный потенциал; пахотные земли; стабильность; факторы влияния; охрана пахотных земель

Introduction

Food security is a matter of paramount importance to the any nation [1;2]. As the world undergoes profound changes unseen in a century, the instability of global food markets is intensifying, and uncertainties regarding the quantity and quality of food supply further increase the potential risks [3]. Although China is a major agricultural country, it suffers from a scarcity of arable land per capita, and its agricultural foundation remains relatively weak. The interaction between the basic national condition of a large population with limited arable land and the changing external environment poses severe challenges to food security [4]. In recent years, China has implemented the strategy of “storing grain in the land and storing grain in technology,” vigorously promoted the construction of high-standard farmland, and steadily enhanced its comprehensive grain production capacity. The No. 1 Central Document of 2023 prioritizes the task of “ensuring stable production and supply of grain and key agricultural products,” explicitly setting the national grain output target at over 650 million tons. Against this backdrop, ensuring food security has become a major issue for safeguarding national security and socioeconomic stability. Investigating the factors influencing the stability of cultivated land productivity is of great significance for achieving sustainable and balanced grain output [5].

Early research in China focused on natural background conditions: Yao Yuan et al. proposed that soil salinity inhibits productivity [6]; Chen Yanhua et al. found that organic matter content contributes significantly to productivity [7]. As research progressed, scholars began to emphasize the influence of human activities and policy systems, discovering that socioeconomic factors such as fertilizer input [8], cropping structure [9], and other factors interact with natural conditions to jointly affect productivity.

Regarding methods for assessing cultivated land productivity, international research has largely relied on crop simulation techniques. For instance, Schellberg J used trend extrapolation to characterize yield evolution patterns [10], De Wit C.T. laid the theoretical foundation for dynamic crop growth simulation [11], the

WOFOST (WOrld FOod STudies) model has been widely applied in land evaluation and yield prediction [12], and the DSSAT (Decision Support System for Agrotechnology Transfer) model enables precise identification of factors affecting productivity at the field scale [13]. Early domestic research in China was primarily based on agricultural land classification and grading results, with Wang Guoqiang et al. [14] systematically exploring the technical pathways for productivity assessment. With the advancement of remote sensing technology, assessment approaches based on vegetation NPP (Net Primary Production) have become a research focus. Guo Zhixing et al. proposed NPP as an effective indicator of farmland productivity [15]; Yan Junxia et al. validated the feasibility of using NPP to characterize cultivated land quality [16]; Liu Xue et al. found a significant correlation between NPP and crop yield [17]. Yanyan Pei et al. employed the CASA (Carnegie–Ames–Stanford Approach) model to calculate NPP and characterize productivity [18], while Chen Yanlin et al. used EOS (Earth Observing System) with MODIS-EVI (Moderate Resolution Imaging Spectroradiometer) data to evaluate cultivated land productivity [19].

Regarding research on factors influencing cultivated land productivity, international studies have often focused on macro-level natural factors. Hoobler B.M. identified light, temperature, precipitation, and soil as key determinants of production potential [20]; Welch J.R. et al. found that rising temperatures can lead to yield reductions [21]; Pooya M.R. emphasized the impact of water supply on yield [22]; Wade J. noted that improving cultivated land quality is a core pathway to increasing yield [23]; Qiao L. found that increasing soil organic matter and available phosphorus content enhances yield stability [24]; Min et al. note the role of geographic information systems (GIS) in the study of the production and economic potential of land [25]. Scientific research has pointed out the need to optimize the size of land plots in order to increase agricultural production [26], and has also identified the main ways to develop international cooperation in the field of sustainable land use [27].

Heilongjiang Province, as a crucial grain production base in China, possesses the largest area of cultivated land resources in the country [28]. However, long-term intensive grain production and irrational farming practices in some regions have led to issues such as the thinning of the black soil layer, a decline in soil organic matter content, and the degradation of soil physicochemical properties, posing challenges to the sustainable use of cultivated land and the stable enhancement of grain productivity [29]. Based on this, this study characterizes cultivated land productivity using NPP and analyzes productivity stability using the coefficient of variation (CV). The multiple regression residual method is employed to spatially analyze the impacts of climate fluctuations and human activities on productivity stability. Furthermore, the study examines how specific influencing factors within climate fluctuations and human activities affect the stability of actual cultivated land productivity in different regions, aiming to provide a scientific basis for the protection and sustainable use of cultivated land in Heilongjiang Province and Northeast China.

Research Methods and Materials

Overview of the Study Area. Heilongjiang Province, the northernmost provincial-level administrative region in China, is located in the northeast of the country. It stretches from 43°25'N in the south to 53°33'N in the north, and from 121°10'E in the west to 135°05'E in the east (Figure 1). The total land area of the province is 473,000 km² (including special regions such as Jiagedaqi and Songling), accounting for approximately 4.9% of China's total land area. Heilongjiang Province has a continental monsoon climate [30]. From south to north, it spans the mid-temperate and cold-temperate zones, while from east to west, it exhibits a gradient transitioning from humid to semi-humid and then to semi-arid conditions. The province experiences low temperatures and little rain in spring, high temperatures and abundant rain in summer, is prone to flooding accompanied by early frost in autumn, and has long, severe winters. Furthermore, the province has a short frost-free period, and significant climatic differences exist between regions. The terrain is characterized by higher elevation in the northwest and southeast and lower elevation in the northeast and southwest, consisting mainly of mountains, tablelands, and plains. The province has a well-developed river system, with major rivers including the Heilong (Amur), Songhua, Wusuli (Ussuri), and Suifen, as well as natural lakes such as Xingkai (Khanka), Jingpo, and Wudalianchi. Data from the Third National Land Survey indicate that the cultivated land area in Heilongjiang Province is 172,000 km², accounting for approximately 36.36% of the province's total land area. The total grain sowing area in the province is approximately 147,400 km², representing 12.40% of the national total. The total grain output of the province has reached 77.88 million tons, accounting for approximately 11.20% of the national output, ranking first in China for fourteen consecutive years.

Data Sources and Preprocessing. Land use data for 2001-2020 were obtained from the China Annual Land Cover Dataset [31] at a spatial resolution of 500 m. NPP data for 2001-2020 were obtained from the MOD17A3 HGF dataset (https://ladsweb.modaps.eosdis.nasa.gov/) provided by NASA (National Aeronautics and Space Administration, USA), with a spatial resolution of 500 m, a temporal resolution of 1 year, and HDF format. Temperature and precipitation data were derived from the China Regional Monthly Temperature and Precipitation Dataset from the National Earth System Science Data Center (http://www.geodata.cn), with a spatial resolution of 1 km. Digital Elevation Model (DEM) and administrative division data were obtained from the website of the Resource and Environmental Science Data Center, Chinese Academy of Sciences (https://www.resdc.cn), with a spatial resolution of 250 m. Cultivated land quality evaluation indicator data were obtained from the Department of Agriculture and Rural Affairs of Heilongjiang Province, soil surveys, and special monitoring of black soil. Data on factors influencing human activities were obtained from statistical yearbooks and the National Bureau of Statistics website (https://www.stats.gov.cn/sj/).

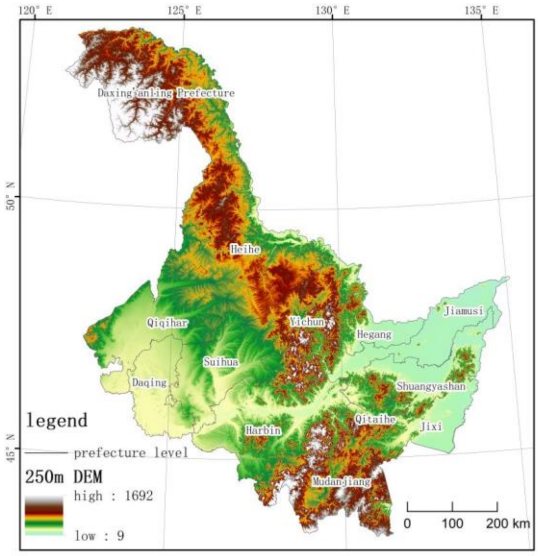

Figure 1. Schematic map of the study area in Heilongjiang Province*

(*2022 Heilongjiang Province DEM data sourced from the website of the Resource and Environmental Science Data Center, Chinese Academy of Sciences).

Data preprocessing mainly included the following. MODIS (Moderate Resolution Imaging Spectroradiometer), a primary remote sensing instrument aboard NASA's Terra and Aqua satellites, is known for its publicly available data, long time series, and short update cycles. The MOD17A3 HGF NPP data for 2001-2020 used in this study correspond to tiles h25v03, h26v03, h26v04, and h27v04. The downloaded data were mosaicked, format-converted, and reprojected using the MODIS Reprojection Tool (MRT). Outliers in the data were removed using ENVI 5.1 software, and the units of the NPP data were converted to $g·C/m^2$. Finally, splicing and clipping were performed using ArcGIS 10.8 to obtain NPP data for Heilongjiang Province. The coefficient of variation for each period was calculated based on ArcGIS software, and the results were classified into three levels (high stability, medium stability, low stability) using the natural breaks classification method. The processing of meteorological climate data (e.g., temperature, precipitation) and topographic data mainly involved steps such as extraction by mask, clipping, reclassification, and projection conversion to ensure the data conformed to the actual conditions of the study area. All data were uniformly processed using the WGS_1984 coordinate system with the Albers projection to facilitate subsequent spatial analysis.

Pearson Correlation Test. The Pearson correlation test is a parametric statistical method used to quantify the degree of linear correlation between two continuous variables and test the statistical significance of that correlation. Its core indicator, the Pearson correlation coefficient (r), ranges from -1 to 1. The specific calculation formula is:

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{X})(y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{X})^2}\sqrt{\sum_{i=1}^{n}(x_i - \bar{Y})^2}} \qquad (1)$$

where $\bar{x}$ and $\bar{y}$ represent the sample means of the two variables, and x_i and y_i represent the independent and dependent variable samples, respectively.

Coefficient of Variation. The coefficient of variation (CV) measures the dispersion of sample data. Spatially, the deviation of NPP from its mean value in different regions directly reflects data stability. A larger CV indicates greater fluctuation and poorer stability; conversely, a smaller CV indicates smaller fluctuation and better stability. The formula for calculating the coefficient of variation of NPP, referencing the literature [32], is:

$$CV = \frac{\sqrt{\sum_{i=1}^{n}(NPP_i - NPP)}}{NPP} \qquad (2)$$

where CV is the coefficient of variation of NPP, NPPi is the NPP value in year i, NPP is the mean NPP over the 20-year period, and n is the corresponding number of study years.

Trend Analysis. Univariate linear regression analysis was used to estimate the interannual dynamics of growing season NPP, where the *slope* of the regression equation represents the rate of interannual change of NPP. The formula for calculating the slope is [33]:

$$slope = \frac{n \times \sum_{i=1}^{n}(i \times NPP_i) - \sum_{i}^{n} i \sum_{i=1}^{n} NPP_i}{n \times \sum_{i=1}^{n} i^2 - \sum_{i=1}^{n} i} \qquad (3)$$

where i represents the integer value of the time series (1≤i≤ n), and the total number of study years n is 20, corresponding to the average growing season NPP for year i. A negative slope indicates a decreasing trend in growing season NPP, while a positive slope indicates an increasing trend. Furthermore, the absolute value of the slope directly reflects the rate of NPP change; a larger absolute value indicates a more significant change.

Multiple Regression Residual Analysis. Multiple regression residual analysis decomposes measured NPP into a climate-influenced component (NPP_{CC}) and a human activity-influenced component (NPP_{HA}) by constructing a statistical model between climatic factors and NPP. This method first calculates a theoretical NPP value (NPP_{CC}) based on the relationship between climate and NPP, and then uses the residual (NPP_{HA}) between the actual value and the theoretical value to represent the intensity of human activity impacts. The specific implementation involves three key steps. First, using growing season NPP data and temporally and spatially interpolated temperature and precipitation data, a bivariate linear regression model is constructed with NPP as the response variable and temperature and precipitation as explanatory variables, and the model parameters are solved. Second, based on the climatic factor data and the established regression equation, the theoretical NPP value (NPP_{CC}), which considers only climatic factors, is calculated to represent the effect of climatic factors on NPP. Finally, the effect of human activities on NPP is quantified by calculating the residual between the measured NPP and NPP_{CC}. The specific calculation formulas are [34]:

$$NPP_{CC} = a \times T + b \times P + c \qquad (4)$$

$$NPP_{HA} = NPP_{obs} - NPP_{CC} \qquad (5)$$

where NPP_{CC} and NPP_{obs} are the NPP predicted value based on the regression model and the NPP observed value based on remote sensing imagery (dimensionless), respectively; a, b, and c are model parameters; T and P are the average growing season temperature (℃) and total precipitation (mm), respectively; and NPP_{HA} is the residual.

Multiple Linear Regression Model. Multiple linear regression is a statistical modeling method used to study the relationship between one dependent variable and two or more independent variables. The goal is to establish a linear equation to predict the value of the dependent variable using the values of the independent variables and understand the independent effect of each independent variable on the dependent variable. Based on this method, this study explores the influence of detailed human activity factors on the stability of cultivated land productivity and quantifies the level of their correlation. The specific calculation formula is:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip} + \varepsilon_i \qquad (6)$$

where y_i is the dependent variable for the i-th observation; x_{i1}, $x_{i2} + \cdots + x_{ip}$ are the independent variables for the i-th observation; β_0 is the intercept term (constant term); β_1, β_2, $\cdots$, β_p are the regression coefficients of the respective independent variables (reflecting the degree of influence on y_i); and ε_i is the random error term.

Results and Discussion

Analysis of the Relationship Between NPP and Cultivated Land Quality. The stability of cultivated land productivity is a core prerequisite for ensuring regional food security, directly reflecting the ability of cultivated land to resist external disturbances and maintain a stable production level. Its level is crucial for the sustainable utilization of cultivated land resources and food security assurance in Heilongjiang Province. NPP is a core indicator for measuring ecosystem productivity [35]. Based on time-series monitoring of NPP, the production potential and changing trends of cultivated land can be assessed. This study utilized the average growing season (May-September) NPP data for Heilongjiang Province from 2001 to 2020 to systematically characterize the spatiotemporal evolution of cultivated land productivity and reveal its interannual fluctuations (Figure 2).

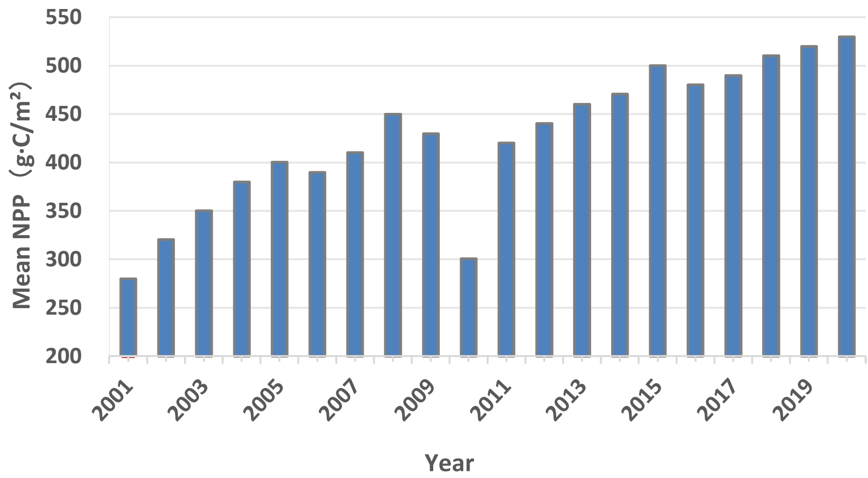

Figure 2. Changes in average NPP values during the growing season in Heilongjiang Province from 2001 to 2020

The average annual growing season NPP values in Heilongjiang Province typically range between 200 and 600 g·C/m². Considering the similarities in natural conditions among different regions and to enhance the reference value of the research results, this study, referencing the principles of the "Comprehensive Physical Regionalization of China" [36] and integrating factors such as topography, climate, hydrology, and vegetation, divided Heilongjiang Province into five regions: Songnen Plain, Sanjiang Plain, Zhangguangcai Range, Eastern Mountains, and Greater and Lesser Khingan Mountains. The prefecture-level cities included in each region are: Songnen Plain (Harbin, Qiqihar, Daqing, Suihua); Sanjiang Plain (Jiamusi, Shuangyashan, Hegang, Qitaihe); Zhangguangcai Range (Mudanjiang); Eastern Mountains (Jixi); Greater and Lesser Khingan Mountains (Heihe, Yichun, Daxing'anling Prefecture). The average growing season NPP values for each region in Heilongjiang Province, from highest to lowest, were: Songnen Plain > Sanjiang Plain > Zhangguangcai Range > Eastern Mountains > Greater and Lesser Khingan Mountains, as shown in Table 1.

Table 1. Comparison of NPP by Region in Heilongjiang Province in 2020

Region	Cultivated land NPP (g·C/m²)
Songnen Plain	475
Sanjiang Plain	468
Zhang Guangcai Ridge	319
Eastern Mountains	213
Greater and Lesser Khingan Mountains	182

Since cultivated land productivity can be calculated based on relevant indices in cultivated land quality databases, analyzing the correlation between NPP and cultivated land quality indicators can serve as a basis for validating the feasibility of using NPP to represent productivity [37]. Black soil quality monitoring indicators vary by land use type. Based on the classification of land use types in Heilongjiang Province according to the province's Major Function Oriented Zone Planning, evaluation indicators were developed for cultivated land (including dryland and paddy field). The primary indicators are soil thickness, soil nutrients, soil pH, and soil erosion. Secondary indicators are classified as mandatory or optional (Tables 2, 3). The mandatory indicators for dryland and paddy fields are consistent. Therefore, the indicators selected for this study include: soil thickness (soil body thickness, black soil layer thickness), soil nutrients (organic matter, total nitrogen, total phosphorus, total potassium, available nitrogen, available phosphorus, available potassium), and soil pH [38].

Table 2. Indicators for evaluating the quality of dryland in Heilongjiang Province

Indicator	Notes	Indicator	Notes
Soil depth	Required	Available phosphorus	Required
Black soil layer thickness	Required	Available potassium	Required
Organic matter	Required	pH	Required
Total nitrogen	Required	Trace elements	Optional
Total phosphorus	Required	Cation exchange capacity	Optional
Total potassium	Required	Slope gradient	Optional
Available nitrogen	Required	Erosion area	Optional

Table 3. Indicators for evaluating the quality of paddy land in Heilongjiang Province

Indicators	Notes	Indicators	Notes
Soil depth	Required	Available nitrogen	Required
Black soil layer thickness	Required	Available phosphorus	Required
Organic matter	Required	Available potassium	Required
Total nitrogen	Required	pH	Required
Total phosphorus	Required	Trace elements	Optional
Total potassium	Required	Cation exchange capacity	Optional

The evaluation indicators and weightings for cultivated land quality in Heilongjiang Province follow the "Technical Specification for Black Soil Quality Evaluation". Based on unified monitoring of mandatory indicators in each region, appropriate additional indicators can be added according to actual needs. Accordingly, this study consolidates soil thickness, soil nutrients, pH, and erosion status (which characterize core black soil properties) into a primary indicator termed "natural background," while also considering degradation risks and protection technologies. Soil erosion leads to black soil degradation and productivity fluctuations, while salinization limits ecological adaptability. As a core measure for black soil protection, high-standard farmland construction enhances water and nutrient retention capacity and increases organic matter through straw return, thereby stabilizing productivity. These two categories of factors reflect, respectively, the constraints of the natural background and the human capacity to regulate degradation risks. Combined with regional black soil degradation characteristics and protection policies, they provide a basis for decision-making on cultivated land productivity stability. Therefore, this study adds two categories of indicators - degradation risk and technology application—in addition to the natural background. The overall evaluation indicators and weights for cultivated land quality in Heilongjiang Province in 2020 are shown in Table 4. The weighted scores for cultivated land quality in each region were calculated using the entropy weight method.

The weighted scores for each region were combined into a comprehensive score and ranked. This ranking was then compared with the ranking of cultivated land NPP to analyze the correlation between cultivated land quality and NPP, thereby assessing the feasibility of using NPP to represent cultivated land productivity. Table 5 shows that the ranking of comprehensive cultivated land quality scores across regions in Heilongjiang Province is generally consistent with the ranking of average cultivated land NPP values. Both rankings follow the order: Songnen Plain > Sanjiang Plain > Zhangguangcai Range > Eastern Mountains > Greater and Lesser Khingan Mountains, indicating a positive correlation. Cultivated land quality assessment not only provides a theoretical basis for improving productivity stability but also identifies limiting factors in each region. For example, the limiting factors in the high-productivity Songnen Plain and Sanjiang Plain are salinization and soil acidification, respectively. The medium-productivity Zhangguangcai Range is constrained by a thin topsoil layer combined with strong acidity. The low-productivity regions, such as the Eastern Mountains and the Greater and Lesser Khingan Mountains, face pressure from soil erosion and insufficient available phosphorus compounded by low effective accumulated temperature, respectively.

Table 4. Indicators and weights for evaluating the quality of cultivated land in Heilongjiang Province

Primary indicator	Secondary indicator	Weighting
	Soil depth	8%
	Black soil layer thickness	12%
	Organic matter	10%
	Total nitrogen	5%
	Total phosphorus	4%
	Total potassium	3%
	Available nitrogen	5%
	Available phosphorus	4%
	Available potassium	4%
	pH	5%
Risk of regression	Proportion of land affected by soil erosion	15%

	Proportion of land affected by salinisation	10%
Technological Applications	Coverage rate of high-standard farmland	8%
	Straw return rate	7%

Combining the analysis of the relationship between cultivated land quality and NPP, this study confirms that NPP can serve as an effective indicator of cultivated land productivity in Heilongjiang Province; cultivated land productivity is obtained through NPP calculation. Concurrently, the coefficient of variation (CV) was used to quantify the stability of cultivated land productivity. Based on the time-series NPP data for the growing season in Heilongjiang Province from 2001 to 2020, combined with natural breaks analysis and regional division, the spatiotemporal characteristics of cultivated land productivity stability were systematically analyzed.

The study focused on the unchanged cultivated land in Heilongjiang Province (approximately 165,200 km²). From 2001 to 2020, the stability values (CV) for cultivated land productivity in this area ranged from 0.00 to 3.00, primarily concentrated between 0.07 and 0.11. Referring to relevant research standards, the natural breaks method was used to classify stability into three levels: CV $\leqslant$ 0.07 (high stability), 0.07 < CV $\leqslant$ 0.11 (medium stability), and CV > 0.11 (low stability).

Table 5. Comprehensive score of cultivated land quality and NPP values by region in Heilongjiang Province

Sort	Region	Comprehensive score for arable land quality	Cultivated land NPP (g·C/m²)	The primary limiting factor
1	Songnen Plain	0.844	475	Salinisation (pH7.8)
2	Sanjiang Plain	0.843	468	Soil oxidation (pH5.9)
3	Zhang Guangcai Ridge	0.670	319	Shallow ploughing depth (18 cm) + highly acidic (pH5.5)
4	Eastern Mountains	0.564	213	Soil erosion (63%)

5	Greater and Lesser Khingan Mountains	0.538	182	Low accumulated temperature + deficiency in available phosphorus

The stability of cultivated land productivity in Heilongjiang Province exhibited a distinct pattern of being higher in the east and lower in the west, with significant regional differences. High-stability areas were mainly concentrated in the Sanjiang Plain, Eastern Mountains, and Zhangguangcai Range. Mudanjiang City had the highest proportion of high-stability cultivated land in the province, at 67.81%. Medium-stability areas were widely distributed across nine prefecture-level cities; the Daxing'anling Prefecture and Hegang City had medium-stability cultivated land proportions of 83.48% and 73.51%, respectively. Low-stability areas were mainly concentrated in the western and southwestern parts of the Songnen Plain. Qiqihar City had a particularly high proportion of low-stability cultivated land, reaching 92.96%, indicating the most severe productivity fluctuations. Looking at the regional standard deviation, the Songnen Plain and Sanjiang Plain showed larger stability fluctuations, while the Zhangguangcai Range and Greater and Lesser Khingan Mountains showed smaller fluctuations, further confirming the spatial distribution differences (Table 6).

Table 6. Changes in the area of different cultivated land productivity stability levels by region in Heilongjiang Province from 2001 to 2020

Regional division		Stability					
		High stability		Medium stability		Low stability	
		Area/km²	Rate/%	Area/km²	Rate/%	Area/km²	Rate/%
Songnen Plain	Harbin	3423.29	15.23	11586.37	51.55	7464.53	33.21
	Qiqihar	4.65	0.02	2082.74	7.03	27559.83	92.96
	Daqing	0.81	0.01	1260.55	12.73	8637.81	87.26
	Suihua	106.66	0.51	4626.67	22.13	16172.64	77.36
Sanjiang Plain	Jiamusi	7365.14	36.25	10506.22	51.70	2448.78	12.05
	Shuangyashan	4470.92	39.56	5989.04	53.00	840.97	7.44
	Hegang	1023.39	16.87	4458.19	73.51	583.01	9.61
	Qitaihe	746.63	27.34	1811.64	66.35	172.32	6.31
Zhang Guangcai	Mudanjiang	6322.15	67.81	2898.46	31.09	102.62	1.10
	Jixi	4582.23	40.90	6111.05	54.54	511.09	4.56

Ridge Eastern Mountains							
Greater and Lesser Khingan Mountains	Heihe	860.57	4.63	12011.00	64.57	5731.27	30.81
	Yichun	294.33	13.43	1459.33	66.61	437.15	19.95
	Greater Khingan Mountains	46.46	8.74	444.02	83.48	41.41	7.79

Identification of Influencing Factors. This study used the linear growth rates of NPPcc and NPP_{HA} to quantify changes in cultivated land productivity stability under the dual effects of growing season climate fluctuations and human activities, respectively. Positive values indicate that climate or human activities positively promote the stability of cultivated land productivity, thereby positively affecting vegetation recovery. Conversely, negative values indicate that these factors may lead to a decrease in the stability of cultivated land productivity, hindering vegetation restoration. "CC & HA" represents the combined effect of climate fluctuations and human activities; "CC" and "HA" represent the effect of climate fluctuations or human activities on the stability of cultivated land productivity, respectively. The contribution rate of each influencing factor type is calculated by the ratio of the remote sensing observation trend rate, the bivariate regression prediction trend rate, and the residual trend rate. If influenced only by climate fluctuations, the climate fluctuation contribution rate is 100%; conversely, if influenced only by human activities, the human activity contribution rate is 100% (Table 7).

Table 7. Criteria for determining influencing factors of NPP and calculation of contribution rates*

Slope (NPP_{obs})[a]	Driving factors	Classification criteria of driving factors		Contribution rate of driving factors（%）	
		Slope (NPP_{CC})[b]	Slope (NPP_{HA})[c]	Climate fluctuation	Human activities
＞0	CC&HA	＞0	＞0	$\frac{slope(NPP_{CC})}{slope(NPP_{obs})}$	$\frac{slope(NPP_{HA})}{slope(NPP_{obs})}$

	CC	＞0	＜0	100	0
	HA	＜0	＞0	0	100
＜0	CC&HA	＜0	＜0	$\frac{\mathrm{slope}(NPP_{CC})}{\mathrm{slope}(NPP_{obs})}$	$\frac{\mathrm{slope}(NPP_{HA})}{\mathrm{slope}(NPP_{obs})}$
	CC	＜0	＞0	100	0
	HA	＞0	＜0	0	100

* a, b, and c refer to the trend rate of NPPobs based on remote sensing data, the trend rate of NPP_{CC} based on bivariate regression analysis, and the trend rate of growing season NPP residuals, respectively; b and c represent NPP change trends under the influence of climate fluctuations and human activities, respectively.

The stability of cultivated land productivity in Heilongjiang Province is affected by both climate fluctuations and human activities. In some regions, either climate fluctuations or human activities dominate, and significant spatial heterogeneity exists in the intensity of the effects of different factors. Under the combined effect of climate fluctuations and human activities, productivity stability is promoted on approximately 20.82% of cultivated land and weakened on approximately 38.50%. Both promotion and weakening effects are distributed across the Sanjiang Plain, Songnen Plain, Eastern Mountains, Zhangguangcai Range, and Greater and Lesser Khingan Mountains. Under the influence of climate fluctuations alone, productivity stability is promoted on approximately 4.12% of cultivated land, concentrated in the central part of the Greater and Lesser Khingan Mountains, the southern part of the Zhangguangcai Range, and the southeastern part of the Eastern Mountains; it is weakened on approximately 5.36% of cultivated land, distributed in parts of the Songnen Plain, Greater and Lesser Khingan Mountains, and Zhangguangcai Range. Under the influence of human activities alone, productivity stability is promoted on approximately 15.69% of cultivated land, mainly distributed in the Songnen Plain but relatively scattered; it is weakened on approximately 15.51% of cultivated land, mainly distributed in the western and southern parts of the Sanjiang Plain and the eastern part of the Songnen Plain. Comprehensive analysis indicates that the combined influence of climate fluctuations and human activities is more widely dispersed and covers a larger area, while the dominance of human activities or climate fluctuations is more concentrated and covers a smaller area (Figure 3). The influencing factor types, ranked by contribution, are: human activities and climate fluctuations combined > human activities alone > climate fluctuations alone.

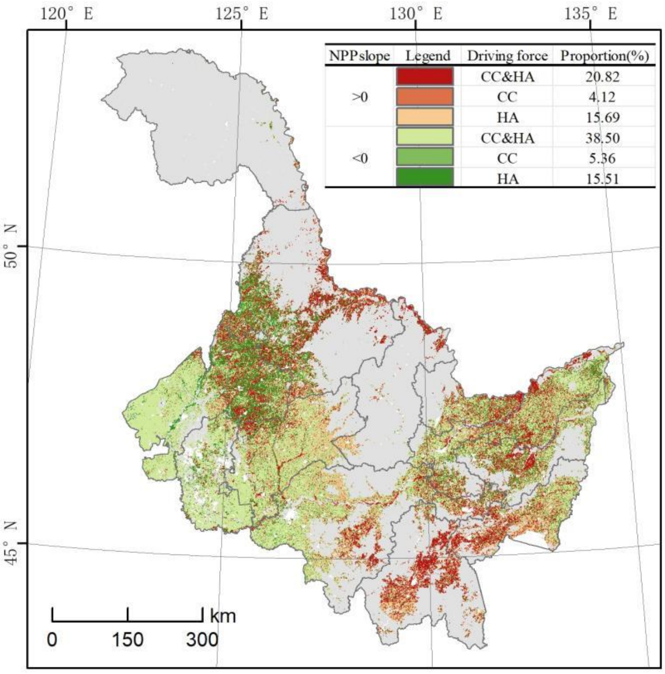

Figure 3. Types and distribution of influencing factors of changes in the stability of cultivated land productivity in Heilongjiang Province

Analysis of Climatic Influencing Factors. Natural background indicators are inherent attributes formed in each region during long-term geological evolution and ecological processes, representing the "innate foundation" of regional cultivated land quality. Their characteristics are primarily determined by stable factors such as historical soil-forming conditions and topography, reflecting the inherent soil baseline status of different regions rather than dynamic impacts of short-term climate change. As core elements of climate change, temperature and precipitation are key external drivers of dynamic changes in cultivated land quality and productivity. Their fluctuations are not only critical for the stability of cultivated land productivity but are also closely related to extreme weather events [39]. The IPCC report indicates that in temperate agricultural regions, over 90% of climate impacts can be attributed to changes in the hydrothermal combination [40].

Concurrently, changes in temperature and precipitation can alter the natural background conditions of cultivated land to some extent [41]. Temperature affects soil development, black soil formation, nutrient content, and pH changes through weathering, microbial activity, and vegetation effects; high temperatures accelerate weathering but also promote organic matter decomposition and salt accumulation. Precipitation regulates soil body maintenance and nutrient distribution through leaching or eluviation; moderate amounts increase organic matter, while excess leads to loss, acidification, or alkalinization. Acting synergistically, temperature and precipitation shape soil properties through physical, chemical, and biological processes, and their specific effects on different soil indicators exhibit regional differentiation due to climatic differences. Therefore, in the cultivated land quality assessment section, this study evaluates based on natural background indicators, while in the analysis of factors influencing the stability of cultivated land productivity, temperature and precipitation are selected as key indicators of climate fluctuation.

Methodologically, this study analyzed the stability of cultivated land productivity by constructing the coefficient of variation (CV). Since the stability value reflects the overall situation over 20 years and cannot be directly linked to climate data from a single year, the study used the deviation (sum of squares of deviations) of interannual productivity from the multi-year trend as a measure of stability. This indicator is positively correlated with CV. This indicator was analyzed for correlation with temperature and precipitation, respectively. In correlation tests, a P-value (Sig. value or significance value) less than 0.01 indicates at least 99.00% confidence in the occurrence, while a P-value less than 0.05 (and greater than 0.01) indicates at least 95.00% confidence. A P-value < 0.01 or < 0.05 indicates statistical significance. Based on significance and correlation analysis conducted for Heilongjiang Province, significance values ranged from 0 to 0.99, with areas where "P-value < 0.01" and "P-value > 0.05" together accounted for up to 90.00% of the total area of Heilongjiang Province. Consequently, a significant correlation exists between the stability values of cultivated land productivity and both temperature and precipitation. This study classifies the correlations into two types: positive and negative.

The correlation between cultivated land productivity stability values and temperature ranged from -0.79 to +0.79, and with precipitation from -0.81 to +0.85. Influenced by differences in natural background and human activities, the effects of temperature and precipitation on productivity stability exhibit regional differentiation. The results indicate that not all regions show the pattern "higher temperature or more precipitation leads to more stable cultivated land productivity." Temperature and precipitation need to be within a suitable range for regional cultivated land cultivation (the suitable temperature range for most cultivated land is approximately 10-25℃); exceeding this range produces adverse effects, a characteristic consistent with the principle of diminishing returns. Using the correlation analysis method, this study explored the positive and negative effects of temperature and precipitation on cultivated land productivity stability in different regions. The results show that in most of the Songnen Plain, cultivated land productivity stability is positively correlated with temperature and negatively correlated with precipitation, indicating that this region has a higher demand for temperature for productivity stability and requires moderate precipitation; excessive precipitation leads to decreased stability. In contrast, within suitable temperature ranges, the Sanjiang Plain, Zhangguangcai Range, and Eastern Mountains show greater stability with higher temperature and precipitation, exhibiting a significant positive correlation with both factors (Figure 4).

Analysis of Human Activity Influencing Factors. Based on data from the National Bureau of Statistics and focusing on the characteristics of grain production in Heilongjiang Province, this study selected 13 indicators from three categories: "agricultural production technology, land management, urbanization and agricultural ecology" to systematically assess the impact of human activities on the stability of cultivated land productivity. Furthermore, based on a multiple linear regression model, the influence of each indicator (independent variable) on the stability of cultivated land productivity (dependent variable, expressed as the

CV value of average growing season cultivated land NPP) was analyzed. Specifically, indicators in the agricultural production technology category (effective irrigated area, total agricultural machinery power, agricultural fertilizer use, pesticide use) reflect the impact of water availability, mechanization, and agricultural input use on cultivated land cultivation. Indicators in the land management category (coverage of high-standard farmland, straw return rate, cultivated land transfer rate, operating scale) represent the effects of land quality improvement, circular agriculture, and management models on the cultivated land system. Indicators in the urbanization and agricultural ecology category (urban expansion rate, disaster-affected area, total sown area of crops, agricultural plastic film use, grain yield per unit area) measure the impacts of urban sprawl, natural risks, production layout, non-point source pollution, and production efficiency on the stability of cultivated land productivity.

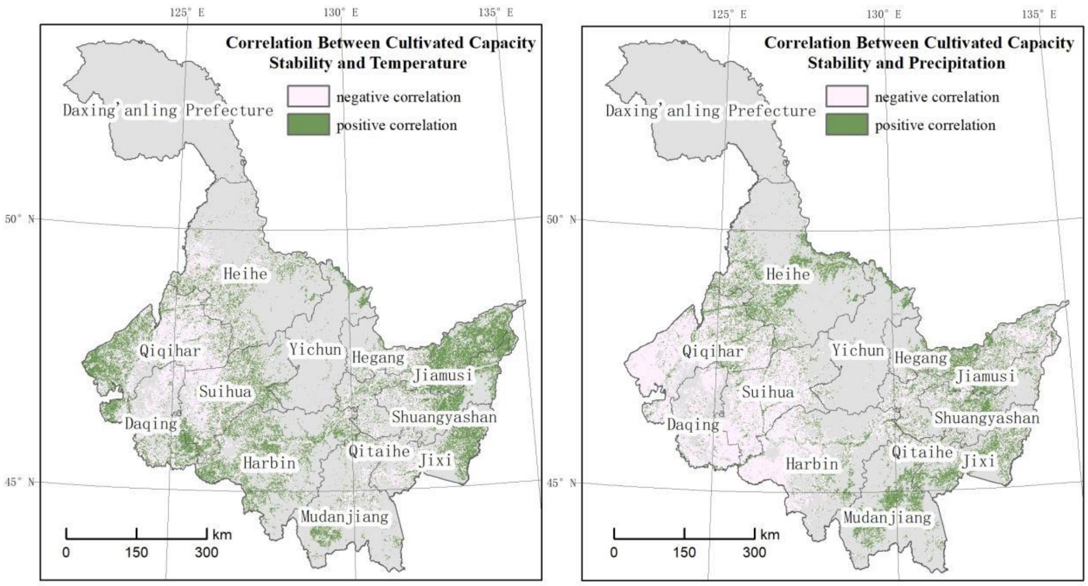

Figure 4. Correlation between the stability of cultivated land productivity and temperature and precipitation in Heilongjiang Province from 2001 to 2020

These elements collectively affect the stability of cultivated land productivity through linear relationships and their quantitative effects. A higher CV value indicates greater fluctuation in cultivated land productivity over the time period and thus lower stability. It follows that when an element shows a positive effect on the stability of cultivated land productivity, the actual meaning is that increasing input of that element leads to a higher CV value, i.e., wider fluctuations and decreased stability. Conversely, if an element shows a negative effect on stability, increasing its input leads to a lower CV value, indicating more stable cultivated land productivity. The correlation heatmap (Figure 5) and analysis results table (Table 8) for factors influencing the stability of cultivated land productivity in Heilongjiang Province show clear differences in the effects of different types of elements.

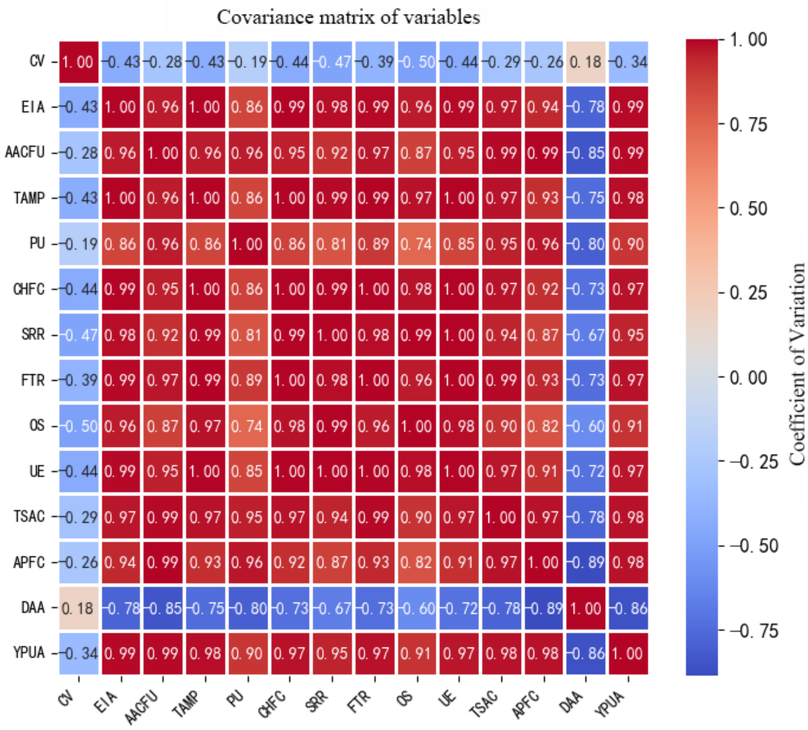

Figure 5. Heatmap of correlations of factors influencing the stability of cultivated land productivity in Heilongjiang Province from 2001 to 2020

1. Agricultural Production Technology Category: Effective irrigated area (EIA) showed a positive correlation with CV, but the regression coefficient was only 0.0045%, indicating that new irrigation in arid areas, constrained by interannual water source variability, leads to a slight amplification of fluctuations. Total agricultural machinery power (TAMP) decreased CV by 0.0083% for every increase of 1 million kilowatts. The mechanism is that mechanization improves the consistency of sowing and harvesting, reducing yield fluctuations caused by delays

in critical agricultural periods. The negative effects of agricultural chemical fertilizer use (AACFU) and pesticide use (PU) stem from moderate inputs reducing the impact of pests, diseases, and nutrient deficiencies.

Table 8. Results of the analysis of factors influencing the stability of cultivated land productivity in Heilongjiang Province

Variable types	Variable	Impact Direction	Regression coefficient	Economic implications
Agricultural production techniques	Effective irrigated area (EIA)	+	0.0045	CV ↑ 0.0045% per +100 kha
Agricultural production techniques	Total Agricultural Machinery Power (TAMP)	-	0.0083	CV ↓ 0.0083% per +100 MW
Agricultural production techniques	Agricultural chemical fertiliser usage (AACFU)	-	0.5117	CV ↓ 0.5117% per +10 kt
Agricultural production techniques	Pesticide usage (PU)	-	4.3806	CV ↓ 4.3806% per +10 kt
Land Management	Coverage rate of high-standard farmland (CHFC)	-	11.2308	CV ↓ 11.2308% per +1%
Land Management	Straw return rate (SRR)	+	18.8474	CV ↑ 18.8474% per +1%
Land Management	Farmland Transfer Rate (FTR)	+	7.2415	CV ↑ 7.2415% per +1%
Land Management	Operating Scale (OS)	-	18.3557	CV ↓ 18.3557% per +10 mu/household
Urbanisation and Agricultural Ecology	Urbanisation rate (UE)	-	1074.7300	CV ↓ 1074.7394% per +1%
Urbanisation and Agricultural Ecology	Area Affected by Disaster (DAA)	+	0.0004	CV ↑ 0.0004% per +100 kha
Urbanisation and Agricultural Ecology	Total Sown Area of Crops (TSAC)	+	0.0038	CV ↑ 0.0038% per +100 kha
Urbanisation and Agricultural Ecology	Agricultural Plastic Film Consumption (APFC)	+	1.5288	CV ↑ 1.5288% per +1 kt
Urbanisation and Agricultural Ecology	Yield per unit area (YPUA)	+	4.4266	CV ↑ 4.4266% per +100 kg/ha

2. Land Management Category: For every 1% increase in the coverage of high-standard farmland (CHFC), CV decreased by approximately 11.23%. This is because field consolidation and improved irrigation and drainage systems reduce the risks of flooding and drought. With an increase in operating scale (OS), farmers are more likely to adopt large-scale production technologies, thereby reducing yield differences between plots. Conversely, straw return rate (SRR) and cultivated land transfer rate (FTR) showed positive correlations with CV. Insufficient decomposition of straw during the initial stages of return can compete with crops for nitrogen, causing short-term yield reductions and fluctuations. When the transfer rate increases, short-term lessees, seeking immediate returns, may reduce investment in soil fertility maintenance, leading to unstable yields.

3. Urbanization and Agricultural Ecology Category: For every 1% increase in the urban expansion rate (UE), CV decreased drastically by approximately 1074.74%. The mechanism is that construction land encroaches on contiguous farmland, forcing the remaining cultivated land into a fragmented distribution. Edge plots are more susceptible to disturbance from human activities, significantly amplifying yield fluctuations. The negative correlation between disaster-affected area (DAA) and CV reflects that the cultivated land eliminated after a disaster often already has weak disaster resistance; thus, the average stability of the remaining cultivated land is paradoxically "improved." Total sown area of crops (TSAC) and agricultural plastic film use (APFC) showed positive correlations with CV, indicating that excessively expanding the planting area or overusing plastic film can lead to soil degradation and micro-environmental imbalance, increasing interannual yield fluctuations.

In summary, it is important to clarify that elements causing a decrease in the stability of cultivated land productivity are not necessarily detrimental to the increase of cultivated land productivity. Some of these elements may positively contribute to productivity enhancement. The "instability" they cause means that within a certain growth cycle, increasing the input of such an element causes the change amplitude of cultivated land productivity to exceed the average fluctuation range, which could be either an increase or a decrease in productivity. In short, the core effect of such elements is to alter the "degree of fluctuation" in productivity. When the fluctuation amplitude exceeds the average, it manifests as a decrease in the stability value, which is a separate evaluation criterion from whether the element is beneficial to productivity increase. Therefore, enhancing the stability of cultivated land productivity requires focusing on the following measures. In agricultural production technology, efforts should focus on improving the level of mechanization and optimizing the structure of agricultural inputs. In land management, the key is the rational planning of high-standard farmland construction and operating scale, while scientifically promoting measures like straw return. In urbanization and agricultural ecology, urban expansion should be strictly controlled, disaster resistance capacity enhanced, and planting structures and input models optimized to reduce cultivated land productivity fluctuations.

Conclusions

1. Using NPP to characterize cultivated land productivity is feasible. This study focused on approximately 165,200 km² of cultivated land in Heilongjiang Province that did not undergo land use type change from 2001 to 2020 as the scope for productivity stability research, analyzing the relationship between NPP and cultivated land quality. The results confirmed the scientific validity and feasibility of using NPP to characterize cultivated land productivity at the macro scale. Furthermore, the coefficient of variation of cultivated land NPP was calculated to characterize the stability of cultivated land productivity, providing a reliable data basis for subsequent stability assessment.

2. The impacts of climate fluctuations and human activities on the stability of cultivated land productivity exhibit significant spatial heterogeneity and phase characteristics. Based on analytical methods such as multiple regression residuals, the influencing factors on cultivated land productivity stability were classified into three types: climate fluctuations alone, human activities alone, and the combined effect of climate fluctuations and human activities. Among these, the combined effect of human activities and climate fluctuations has a significant influence,

followed by the individual influence of human activities or climate fluctuations alone. Regarding the dominant factors, climate fluctuations dominate in the high-latitude cold regions, while human activities dominate in regions such as the south-central Songnen Plain and the Eastern Mountains.

3. Concerning climatic factors, the stability of cultivated land productivity in the Songnen Plain is positively correlated with temperature and negatively correlated with precipitation. In the Sanjiang Plain and Eastern Mountains, it is positively correlated with both temperature and precipitation. Concerning human activity factors, elements related to agricultural production technology, land management, urbanization, and agricultural ecology significantly affect the stability of cultivated land productivity. Effective irrigated area, straw return rate, cultivated land transfer rate, disaster-affected area, total sown area of crops, agricultural plastic film use, and grain yield per unit area tend to increase CV and decrease stability. Conversely, total agricultural machinery power, agricultural chemical fertilizer use, pesticide use, coverage of high-standard farmland, operating scale, and urban expansion rate tend to decrease CV and increase stability.

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