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RESEARCH ARTICLE

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Spatial–temporal pattern of cultivated land productivity based on net primary productivity and analysis of influencing factors in the Songhua River basin

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Abstract

Inefficient utilization puts the productivity of cultivated land in a low development state. The key challenge for the efficient utilization of cultivated land is to clarify how various factors affect the spatial differentiation pattern of cultivated land productivity (CLP), to improve food production. However, evaluating the impact of the intensity and direction of CLP on a large-scale is a difficulty and there is a gap in knowledge. In this study, we used net primary productivity (NPP) to calculate the productivity of cultivated land and reveal its spatial differentiation. Also, this study examined the spatio-temporal heterogeneity of CLP and determined the effect intensity and the direction of effect of various factors on productivity, using the Songhua River basin (SRB) in China as a research case. We used genetic algorithms to modify and improve a neural network model of factor dimensionality reduction, combined with path analysis, cluster analysis, and regression analysis, to identify the main factors impacting CLP, synergies between these factors, and effect intensity and direction. The results showed that: (1) the area of cultivated land in SRB decreased, but the NPP of cultivated land area increased, during 2000–2020; (2) spatially, NPP was relatively low in the middle of the basin and gradually increased towards the periphery; (3) The main positive factors were the normalized difference vegetation index (NDVI), slope, precipitation, evapotranspiration, and total nitrogen, while the main negative factors were temperature, ratio vegetation index, and total phosphorus. Individual principal factors and the synergy between these factors gave CLP different temporal and spatial heterogeneity. Collaborative management of the threshold range of various influencing factors would improve the CLP. This novel information on spatial–temporal differentiation and factors influencing CLP can be important in formulating science-based and feasible policies for land protection and for improving CLP.

KEYWORDS
cultivated land productivity, cultivated land protection, land use management, net primary productivity, production capacity

1 | INTRODUCTION

Cultivated land is a source of food for human survival and development (Shi et al., 2020). Cultivated land productivity (CLP) refers to the potential capacity for crop yield in a particular region, in a certain period, and under specific natural, economic, social, and technological conditions (Deng et al., 2017). Stability of CLP has always been a matter affecting food security and human livelihoods (Gaupp et al., 2020). Thus, China's National Plan for Increasing Food Production Capacity [(NPIFPC); 2009–2020] refers to food 'production capacity' rather than food 'yield' (Chen, Zhao, et al., 2022). This involves pursuing not only actual increases in yield, but also improvement of cultivated land production capacity (Chen et al., 2019).

Given its strategic importance, there is considerable interest in improving CLP to ensure the sustainability of future food production. However, with recent rapid economic development population and population growth in China, the intensity of exploitation and utilization of cultivated land resources is increasing (Ye et al., 2020). This in turn is causing frequent land-use changes (Girma et al., 2022) and soil fertility decreases (Tsymbarovich et al., 2020), which can lead to a decline in CLP over time. In addition, the productivity of cultivated land in different regions is not consistent, reflecting spatial heterogeneity in soil quality, which could pose difficulties for efforts to improve CLP (Olmo et al., 2016). Therefore, research to clarify the spatial–temporal differentiation in CLP and identify the intensity and direction of factors influencing CLP is urgently needed to improve the productivity of cultivated land.

Research to date has examined spatial–temporal differentiation and influencing factors on CLP using different approaches. The spatial–temporal pattern of CLP has been assessed using different metrics, e.g., correlation with agricultural land gradation (Chen, Lin, et al., 2022), correlation with regional yields (White et al., 2019), and total factor productivity (Han & Zhang, 2020). This has been done using different models, e.g., multivariate statistical models (Döös & Shaw, 1999), agro-ecological zoning (AEZ) methodology (Jiang et al., 2017), enhanced vegetation index (EVI) crop growth curves (Xu et al., 2019), MODIS normalized difference vegetation index (NDVI) data estimation models (Saeed et al., 2017), light-temperature (climate) potential productivity (Song et al., 2014), and crop mechanistic models (Bali & Singla, 2022). These studies have examined in depth the mechanisms affecting crop yield, which is valuable knowledge. However, it is difficult to obtain large-scale, high-precision crop classification data, so these mechanism models often lack generalizability, and some statistical methods are based on the regional scale, which limits expression of heterogeneity on spatial grids.

Research on the factors influencing CLP has mainly focused on individual natural factors such as sunshine (Gopinath et al., 2022), precipitation (Huang et al., 2017), temperature (Pan & Dong, 2018), the thickness of black soil (Gu et al., 2018), organic matter content (Lal, 2020), organic carbon (Luo et al., 2022), carbon fluxes (Ichii et al., 2005), fertilizer (Sinha et al., 2022), salinization degree (Sui et al., 2018), Differential Vegetation Index (DVI) (Franch et al., 2019), landform (Rahmanipour et al., 2014), slope (Montealegre et al., 2022), loss of biodiversity (Cowles et al., 2016), degree of mechanization (Zhu et al., 2019), and irrigation potential (Ozdogan, 2011). However, different combinations of meteorological, climate change, land degradation, and seasonal variations could have a significant combined impact on productivity (Raich et al., 1991). The parent material of soil formation, the climate and the lithology of the watershed were also important for the process of soil formation and productivity (Gong et al., 2021). Human activities (Lyu et al., 2020) such as logging and land use changes for farming and urbanization can also cause major changes in productivity (Kuhnert et al., 2017; Rollinson et al., 2017) and CLP distribution (Riutta et al., 2018). Studies on the influence of specific socio-economic factors on CLP indicate that capital, labour, and policy are also important factors (Paudel et al., 2019; Yang et al., 2020). However, research on the impact of CLP has usually been concentrated on natural factors, with the experimental research generally being carried out with small experimental field blank control, limiting the possibility of expanding to large-scale areas, which was a gap. Meanwhile, these natural, ecological and socio-economic factors are seldom considered together to explore the synergy or trade-off between these cross domain factors.

Large scale regions or watersheds flow through many regions and have a wide range of influences. The resources in different regions are unevenly distributed, which leads to significant regional differences in the distribution of natural, ecological, and social resources in large-scale regions. It is difficult to calculate the CLP of large-scale regions and identify influencing factors. Therefore, the calculation cannot copy the results of small-scale zones or experimental fields. It is difficult to bring regional differences and the heterogeneity of large-scale regional spatial elements into the research framework.

Simulation of CLP from net primary productivity (NPP) has been used for estimating grain yield of cultivated land on a spatial scale (Running et al., 2000), and has been shown to be an effective way to express the spatial–temporal heterogeneity (Gholkar et al., 2014). NPP refers to the accumulation of organic dry matter in crops per unit time and area, calculated as the total amount of organic matter produced by crop photosynthesis minus the remaining part after autotrophic respiration (Bradford et al., 2005). Thus crop yield is directly related to NPP, and CLP can be calculated by inverting the NPP value (Lin et al., 2012). Based on the spatial differentiation of NPP on cultivated land, a spatial distribution pattern with high- and low-yielding fields can be obtained (Ji et al., 2015). This makes it possible to explore a modeling approach using NPP to express CLP when studying the influence characteristics of spatial heterogeneity in large-scale regions.

The Songhua River basin (SRB) is an obvious large-scale region with prominent spatial heterogeneity of CLP and complex influencing factors. The SRB is one of the three largest black soil areas in the world, and also the best-cultivated land in China. It was instrumental to the NPIFPC task of increasing food production in the Northeast region of the SRB by 15 billion kg by 2020 (Yang et al., 2021). However, with the ongoing occupation of land by human beings and the inefficient use of some cultivated land, as well as the constraints imposed by natural ecological and social-economic factors, the productivity of cultivated land in the SRB is under pressure. It is important to assess whether future changes in CLP will affect grain yield and the factors influencing CLP changes.

A new approach is therefore needed to integrate nature, ecology, and society, reflect the spatial heterogeneity of CLP in large-scale areas with the help of remote sensing, and overcome the problem of the difficulty of data acquisition. Also, it may be able to delve into the intensity and direction of influencing factors. Specific objectives of this work were thus to: (1) analyze the spatial differentiation in CLP in the SRB based on NPP changes; (2) perform a combined assessment of the natural, ecological, and socio-economic factors influencing CLP and determine the intensity and direction of effect of the main influencing factors, and (3) explore synergistic/tradeoff effects of individual and composite factors on CLP. The intention was to make an important contribution to improving CLP in practice, achieving sustainable utilization of regional cultivated land, implementing protection policies for cultivated land, and ensuring food security.

2 | MATERIALS AND METHODS

2.1 | Study area

Songhua River basin is an important commercial food base in Northeast China (41°42′ N–51°38′ N, 119°52′ E–132°31′ E) (Figure 1). The total area of SRB is 56.12×10^4 km^2, of which a plains area makes up 21.21×10^4 km^2 and hill areas 34.91×10^4 km^2. The elevation of the basin is 43 - 2667 m with a general trend for higher elevation in the west and east, while the central part is mainly plains. Fertile land and abundant water resources are two major advantages for expansion of agriculture in the SRB. Cultivated land in the SRB currently accounts for nearly 20% of the national cultivated land area in China, and it produces 35% of the maize and soybean grown in the Country, and around one-third of national commodity grain production.

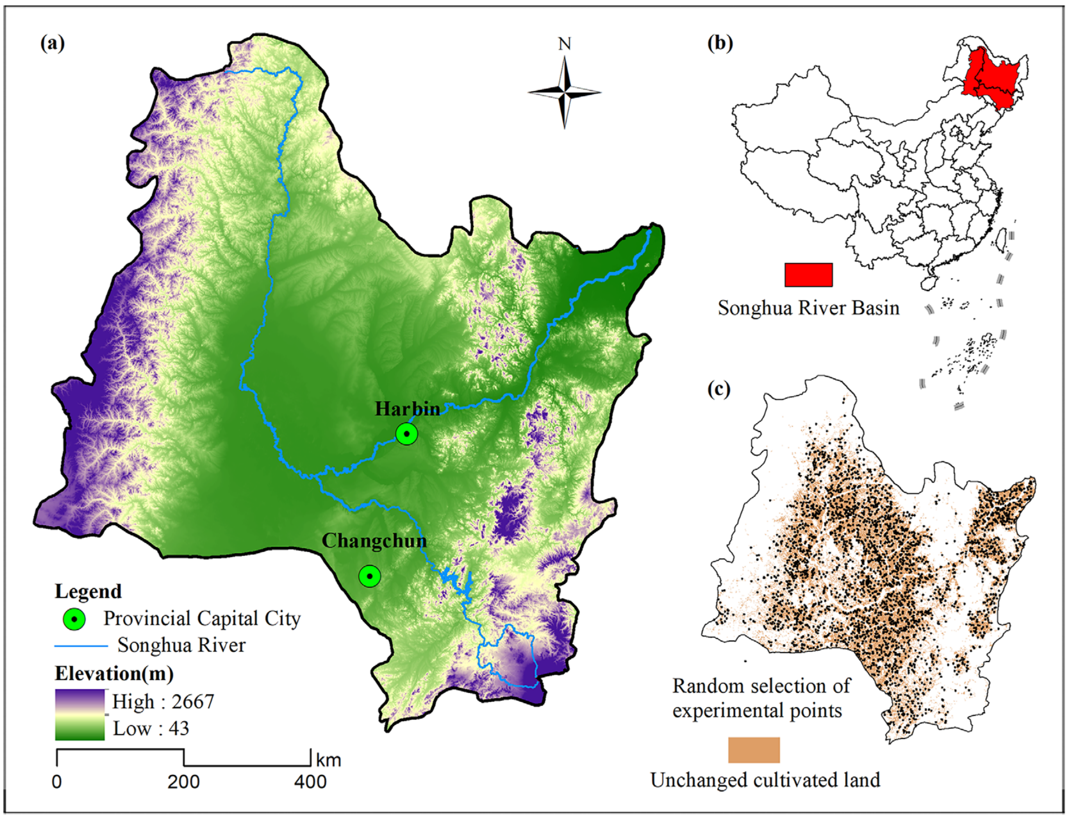

FIGURE 1 (a) Relief map of the basin, (b) location of the Songhua River basin (SRB) in Northeast China, and (c) distribution of unchanged cultivated land in the SRB 2000–2010 and location of randomly selected experimental points. Wiley acknowledges that the borders within the figure are subject to multiple territorial claims [Colour figure can be viewed at wileyonlinelibrary.com]

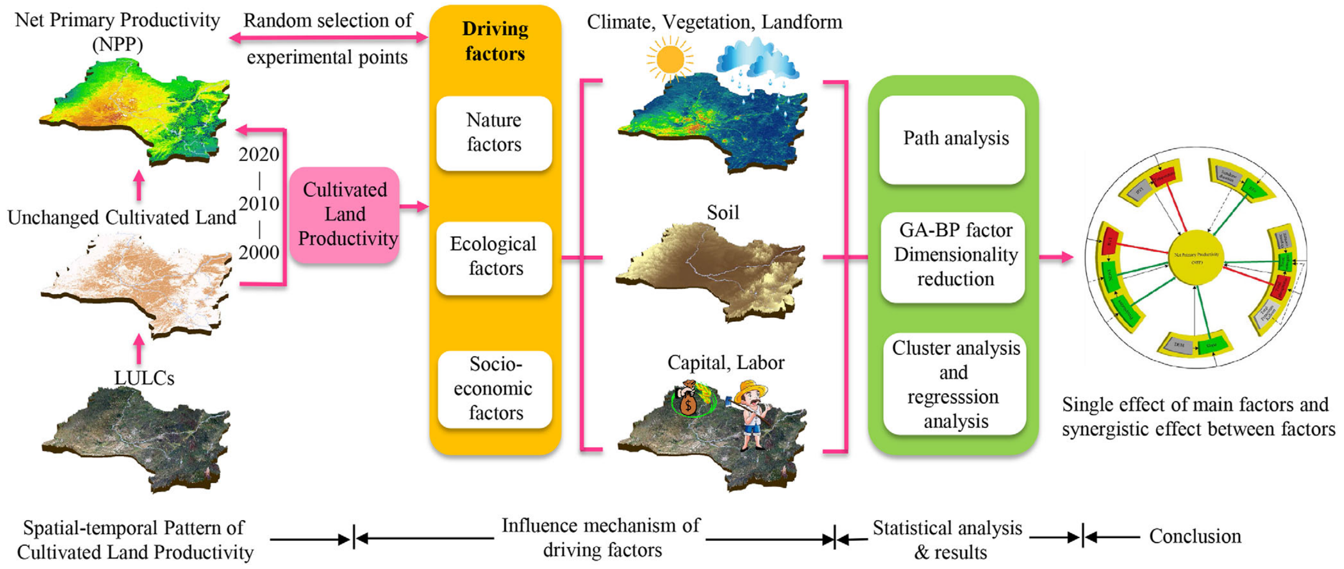

FIGURE 2 The operational framework applied in the present analysis [Colour figure can be viewed at wileyonlinelibrary.com]

2.2 | Operational framework

The operational framework developed for the study is shown in Figure 2. It involved: (1) using land use-land cover (LULC) data to extract the area of unchanged cultivated land in the SRB and calculating the spatio-temporal heterogeneity in CLP based on NPP data. (2) Preparation of data on natural, ecological, and socio-economic aspects. (3) Statistical analysis, including GA-BP [genetic algorithm (GA); back propagation (BP)] factor dimensionality reduction, path analysis, cluster analysis, and regression analysis. (4) Assessment of individual effects of main factors and synergistic effects of different groups of factors.

2.3 | Spatial–temporal pattern of CLP

2.3.1 | Changes in cultivated land

Changes in cultivated land area will inevitably lead to a change in CLP. Based on the characteristics of the SRB and the surrounding region, we chose the years 2000, 2010, and 2020 for analysis of LULC change. We extracted information on pure cultivated land area and calculated the change in cultivated land area in the period. To prevent the impact of change in cultivated land area masking that of the main underlying factors, we did not consider the increase or decrease in CLP caused by an increase or decrease in cultivated land area. Thus in the analysis of CLP we only included pure cultivated land, i.e., land with no change in use type 2000–2020.

2.3.2 | Calculation of CLP from NPP

The NPP products used originated from the MODIS database, which applies the principle of light energy utilization in the process of plant photosynthesis. Values are obtained by simulating a series of plant physiological and ecological processes such as photosynthesis, assimilation and distribution, self-respiration, transpiration, and growth season (Bolinder et al., 2007). NPP can reflect the productivity of cultivated land with a unified scale standard. It avoids the interference of agricultural structure adjustment and crop variety change on the measurement of CLP, which is a very objective indicator of CLP (Wiedmann & Barrett, 2010).

Based on this conclusion, we also verified the relationship between NPP and CLP in the SRB (Part 1 in Appendix S1). We extracted NPP through the cultivated land mask to explore the spatial and temporal heterogeneity and dynamic changes in CLP at grid-scale based on changes in NPP 2000–2020. We then used the spatial random value of NPP to explore factors influencing CLP.

2.4 | Mechanism of influence of driving factors

The productivity of cultivated land is a huge and complex system, with specific functions, that has developed under the long-term influence of natural, ecological, and social-economic factors. The main determinants of grain yield are irrigation (Moradi et al., 2022), cultivated land area (Jiang et al., 2020), fertilizers (Martey et al., 2019), and pesticides (Rahman, 2013). Therefore, these are also the decisive driving factors of CLP.

According to the Chinese Environmental Protection Administration, the maximum amount of pesticides and fertilizer that may be applied in ecological conservation areas is 3 and 250 kg ha^{-1}, respectively (Zhang et al., 2017), which aims to meet the demands of crop production without damaging the ecological environment. The actual amount applied is greater than the standard value, so the degree of application at grid scale can be considered sufficient to meet the needs of growing crops. Hence this indicator was excluded from the productivity calculations. Similarly, irrigation water supplied was assumed to be similar and sufficient at each grid scale, so we only considered the impact of natural precipitation on CLP.

Based on findings in previous studies (Jiang et al., 2015; Song et al., 2014), 25 factors closely related to the productivity of cultivated land were selected for analysis (Table 1). We randomly selected 10,000 points in the SRB, of which 3161 points were on permanent cultivated land (Figure 1c), and then matched the data on influencing factors to the sampling points in the area of unchanged cultivated land. We used the *extract values to points* function in the Spatial Analyst Toolbox from ArcGIS 10.2 software to match the data to random sampling points of cultivated land from the spatial grid. The raster data of spatial distribution of the 25 main factors influencing CLP are provided in Figures S1–S4. Because the ecological soil data originated from the Second National Soil Survey in 2009, we chose 2010 as the baseline research year.

2.5 | Statistical analysis

2.5.1 | Method used for identification of the main factors influencing CLP

In identifying the main factors influencing CLP, we used MATLAB R2016b software for programing and the genetic algorithm (GA) model to modify and improve the back propagation (BP) neural network, in what is called the GA-BP factor dimension reduction method (Ge et al., 2014). Because the GA-BP model has a high fault tolerance to random variables, it can deal with the multicollinearity and dimension of high data. It is convenient to measure the relationship between input variables and output variables, to explain the main influencing factors on the change of CLP.

This method is based on the conventional BP model, where the first step is to optimize and improve the *fitness* function and *codec* function in the GA model, and the second step is to use the improved GA model to optimize the weight and threshold of the BP model (Shen et al., 2020). By installing and employing the genetic algorithm toolbox (GAOT), a GA-BP factor dimension reduction model was established (Figure S9 in Appendix S1).

2.5.2 | Path analysis, cluster analysis, and regression analysis

The theory of path analysis proves that the simple correlation coefficient (r_{iy}) between any independent variable X_i and the dependent variable Y is equal to the sum of the direct path coefficient (P_{iy}) of X_i and Y, and the indirect path coefficient (P_{ij}) of all X_i and Y, which is the total effect of X_i on Y: $r_{iy} = P_{iy} + P_{ij}$.

When many independent variables jointly affect a dependent variable, the importance of each independent variable to the dependent variable is different, and one of the independent variables may act on the dependent variable through other independent variables, which can be represented by indirect path coefficient. For example, the indirect path coefficient of X_i to Y through X_j is: $P_{ij} = r_{ij} \times P_{jy}$.

The basic concept in hierarchical cluster analysis is that variables with similar distances are clustered first and variables with longer distances are clustered later. We used SPSS 21 software to call the *linkage* function, and created a hierarchical cluster tree by the method of the class average. In addition, we used Pearson correlation to measure the interval of the standard. R-cluster analysis was carried out for all influencing factors, and the main influencing factors and their synergistic relationships were grouped.

2.5.3 | Individual effect of main factors and synergistic effects between factors

Synergistic effects are based on multiple regression, the correlation coefficient is decomposed into direct path coefficient (the direct influence of independent variables on the dependent variable) and indirect path coefficient (the indirect influence of independent variables on the dependent variable through other independent variables). The standard coefficient of the regression equation is the direct path coefficient (direct effect), which reflects the single effect of the main factors on cultivated land productivity. Path coefficient multiplied by a correlation coefficient gives us indirect path coefficient (indirect effect), which reflects the synergistic effect of the main factors on CLP. The formula is as follows:

$$r(x,y) = \frac{\mathrm{Cov}(x,y)}{\sqrt{\mathrm{Var}(x)\mathrm{Var}(y)}}$$

$$R^2_{(i)} = R^2_i + \sum_{j \neq i} R^2_{ij} = 2b_i r_{iy} - b^2_i \; (i,j = 1,2,\ldots,p)$$

Where: $r(x,y)$ is the correlation coefficient, Cov(x,y) is the covariance between independent variable x and dependent variable y, Var(x) is the variance of x, Var(y) is the variance of y. $R^2_{(i)}$ reflects the comprehensive decisive effect of x_i on y through the correlation network of x_1, x_2,... x_p. In addition, $R^2_i = b^2_i$ represents the direct determination coefficient of x_i to y; $R^2_{ij} = 2b_i r_{iy}$ represents the indirect determination coefficient of x_i and x_j to y through the correlation path; That is, it includes the decisive effect of x_i on y through x_i, and also includes the decisive effect of x_j on y through x_i. b_i is the partial regression coefficient of x_i; r_{ij} is the correlation coefficient between x_i and x_j; r_{iy} is the correlation coefficient between x_j and y. When $R^2_{(i)} > 0$, it indicates that x_i has an enhanced effect on y, and when $R^2_{(i)} < 0$, x_i has a restrictive effect on y.

Synergism among factors refers to the combined effect of factors on CLP. There are synergies among various factors and they can all jointly affect CLP in the study area, but the magnitude and direction of the synergy are different. There are two aspects regarding the influence of synergies among factors on CLP: one is the influence of synergies among the main factors, which is called synergistic effects 1, and the other is the influence of synergies between other factors and the main factors, which is called synergistic effects 2. The value range of the partial correlation coefficient is (−1,1) among factors, with the larger the absolute value, the greater the degree of partial correlation.

TABLE 1 The 25 main factors influencing cultivated land productivity

Target layer	Feature layers	Sub feature layers	Impact factors	Symbol	Data sources
CLP (NPP) Symbol: Y_{NPP}	Natural factors	Vegetation	Normalized difference vegetationi index (NDVI)	X_{NDVI}	Resource and Environment Data Cloud Platform of the Chinese Academy of Sciences, NDVI = (NIR-R)/(NIR + R), Web: http://www.resdc.cn/
			Difference/environmental vegetation index (DVI/EVI)	X_{DVI}	Geospatial Data Cloud DVI = NIR-R, Web: http://www.gscloud.cn/
			Ratio vegetation index (RVI)	X_{RVI}	RVI = NIR/R, raster calculation from NDVI
		Hydrology and climate	Mean annual precipitation	X_P	National Meteorological Science Data Center Web: http://data.cma.cn/ spatial interpolation
			Mean annual temperature	X_{Temp}	
			Sunshine duration (sun)	X_{Sun}	
			Potential evapotranspiration (ETo)	X_{ETo}	MODIS Global Evapotranspiration Project (MOD 16), Web: https://search.earthdata.nasa.gov/search?q=MOD16A2+V006
		Landform	Digital elevation model (DEM)	X_{DEM}	Geospatial Data Cloud Web: http://www.gscloud.cn/
			Slope	X_{Slope}	Raster calculation from DEM
	Ecological factors	Soil texture	Sand	X_{Sand}	Cold and Arid Region Scientific Data Center Web: http://westdc.westgis.ac.cn/
			Clay	X_{Clay}	
			Silt	X_{Silt}	
		Soil nutrients	Organic content (OC)	X_{OC}	
			Total nitrogen (TN)	X_{TN}	
			Total phosphorus (TP)	X_{TP}	
			Total potassium (TK)	X_{TK}	
		Chemical properties of soil	Topsoil calcium carbonate ($CaCO_3$)	X_{Ca}	
			pH	X_{PH}	
			Pore Available Water Capacity (PAWC)	X_{PAWC}	
			Soil erosion	X_{Se}	Calculation using InVEST model based on the soil erosion equation (USLE)
	Socio-economic factors	Irrigation capacity, transportation, farming convenience	Euclidean distance from a water source to cultivated land	X_{Wc}	Using the *euclidean distance* function in ArcGIS 10.2 software to calculate the distance between cultivated land and water area
			Euclidean distance from the village to cultivated land	X_{Vc}	Using the *euclidean distance* function in ArcGIS 10.2 software to calculate the distance between cultivated land and village
			Euclidean distance from the road to cultivated land	X_{Rc}	Using the *euclidean distance* function in ArcGIS 10.2 software to calculate the distance between cultivated land and road
		Labor and capital investment	Population density	X_{Pop}	Resource and Environment Data Cloud Platform of the Chinese Academy of Sciences, Web: http://www.resdc.cn/
			Population gross domestic product (GDP)	X_{GDP}	

2.6 | Data requirement and preparation

The LULC data used was taken from the global land cover data product service website (http://www.globallandcover.com/) of the National Geomatics Center of China (DOI: 10.11769). The digital elevation map (DEM) data was downloaded from the Geospatial Data Cloud (http://www.gscloud.cn/). The data on soil physical and chemical properties came from the Cold and Arid Region Scientific Data Center (http://westdc.westgis.ac.cn/) (Shangguan et al., 2012). The NPP data came from NASA (National Aeronautics and Space Administration) (https://earthdata.nasa.gov). Spatial grid data on precipitation, sunshine duration, and temperature was obtained through kriging interpolation of ArcGIS 10.2 software (Figure S5), and data on the study area was extracted using the boundary mask for SRB.

A brief summary of these and other relevant data sources used in this study is provided in Table S2. The resolution of all raster layers was 90 m × 90 m. The geographical coordinate system used was GCS_WGS_1984 and the projection was Albers.

3 | RESULTS

3.1 | Changes in cultivated land area

The cultivated land area in SRB in 2000, 2010, and 2020 was $24.32 \times 10^4\ km^2$, $24.18 \times 10^4\ km^2$, and $24.16 \times 10^4\ km^2$, respectively, i.e., it showed a gradual decrease (Figure 3). From 2000 to 2010, the increase in area of newly cultivated land ($0.57 \times 10^4\ km^2$)

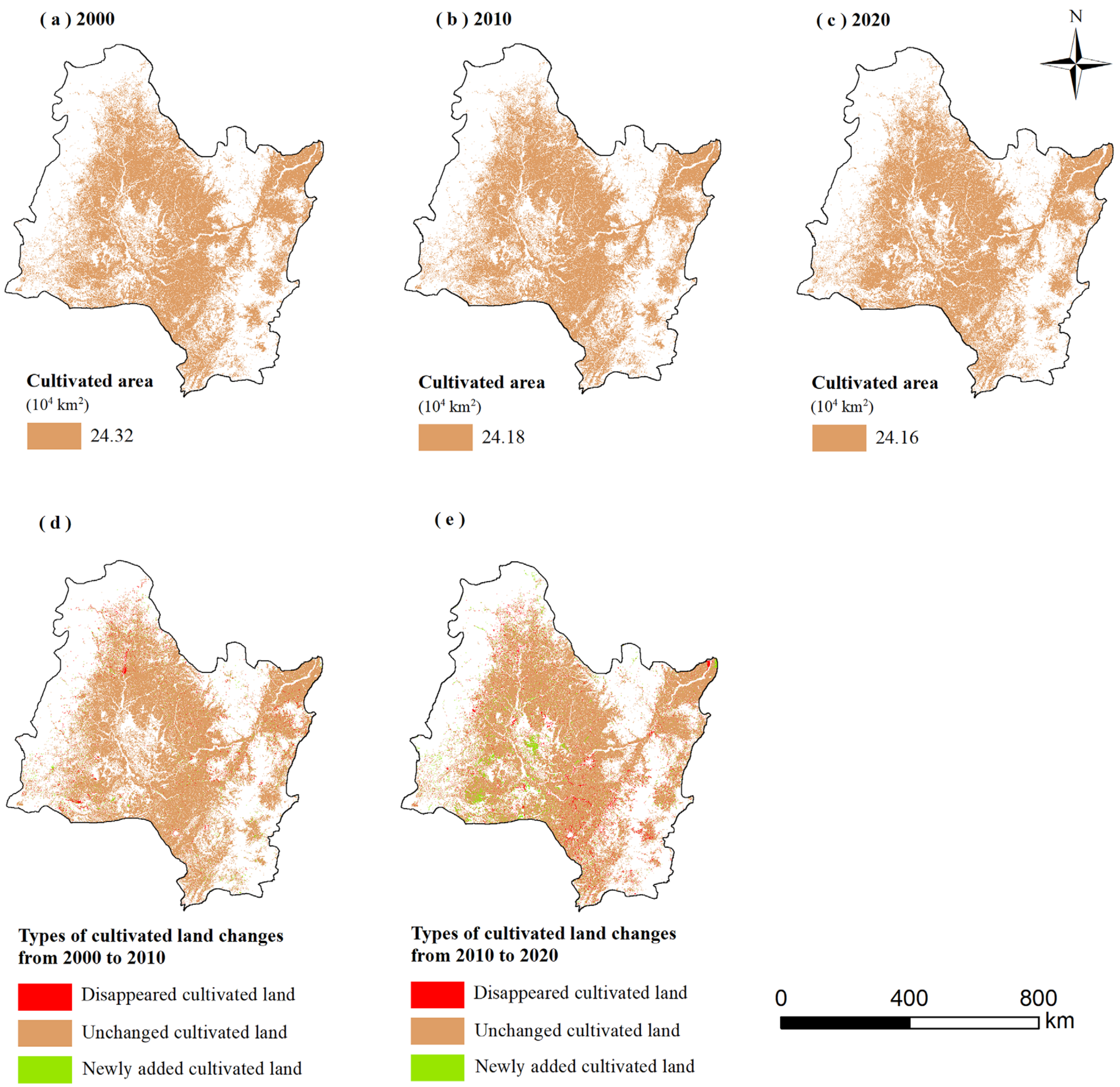

FIGURE 3 Cultivated land area in Songhua River basin in (a) 2000, (b) 2010, and (c) 2020, (d) types of cultivated land changes from 2000 to 2010, and (e) types of cultivated land changes from 2010 to 2020 [Colour figure can be viewed at wileyonlinelibrary.com]

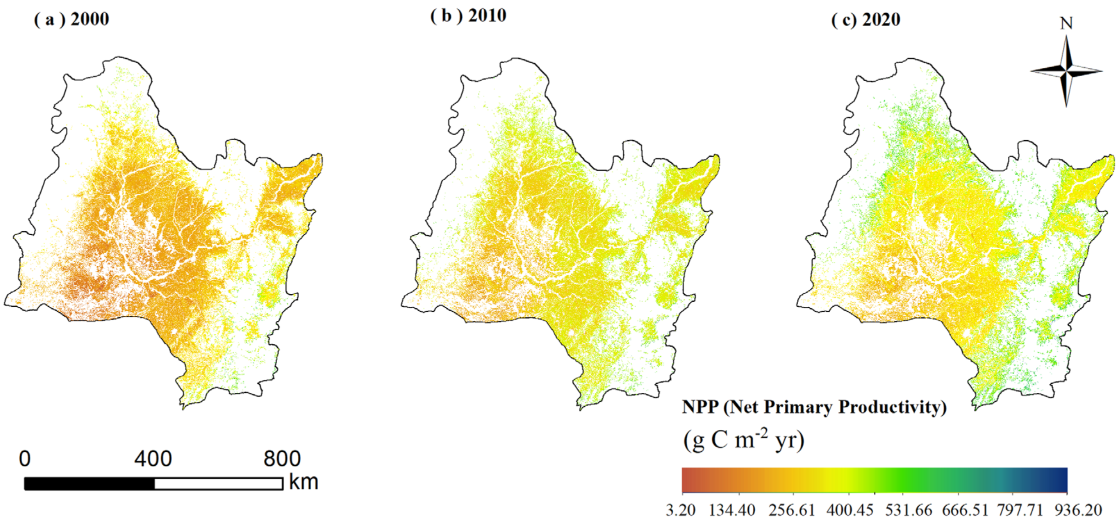

FIGURE 4 Net primary productivity (NPP) in Songhua River basin in (a) 2000, (b) 2010, and (c) 2020 [Colour figure can be viewed at wileyonlinelibrary.com]

was less than the reduction in cultivated land area (0.71×10^4 km^2). From 2010 to 2020 more cultivated land was added than in 2000–2010, but the increase in newly cultivated land area (1.62×10^4 km^2) was still less than the decrease in cultivated land area (1.64×10^4 km^2).

3.2 | Changes in NPP

Spatially, NPP was relatively low in the middle of the basin and gradually increased to the periphery (Figure 4). Thus the productivity of cultivated land was greater at the periphery than that in center of the basin. In terms of time, NPP increased from 2000 to 2020. The total amount of NPP in SRB in 2000, 2010, and 2020 was 6350.56×10^{10} g C, 8172.70×10^{10} g C, and $9007.62 * 10^{10} gC$ 9007.62×10^{10} g C, (Table S3), respectively, that is, so the production capacity of cultivated land also increased in the period.

According to the statistics on random sample points extracted from unchanged cultivated land in 2000, 2010, and 2020 (Figure 5), the average of NPP of random sample points in the SRB in 2000, 2010, and 2020 was 252.56, 329.70, and 361.46 gC m^{-2} (Table S3), respectively. NPP increased annually, confirming that CLP increased in terms of quantity in the period.

3.3 | Intensity and direction of the individual effect of main factors on CLP

The results from the GA-BP factor dimensionality reduction model after optimization and identification indicated that eight factors (NDVI, slope, precipitation, potential evapotranspiration (ETo), temperature, ratio vegetation index (RVI), total phosphorus (TP), and total nitrogen (TN) were the most important factors determining CLP (see Part 3.2 in Appendix S1).

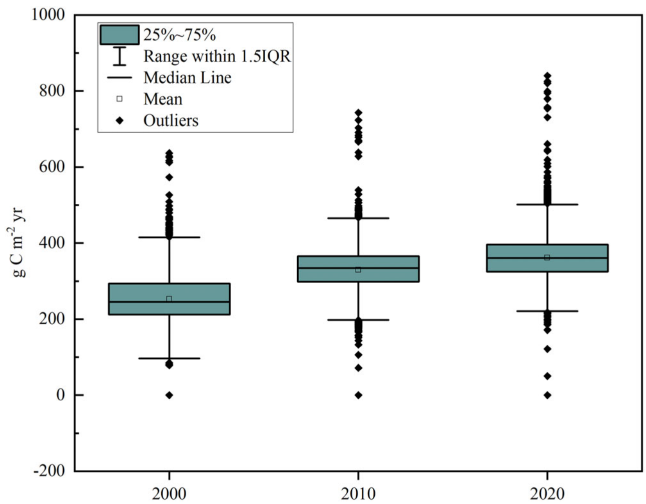

FIGURE 5 Statistics of random sample points for net primary productivity (NPP) in 2000, 2010, and 2020 [Colour figure can be viewed at wileyonlinelibrary.com]

After eliminating the influence of other factors, we calculated the partial correlation coefficient between NPP and these eight main factors (Table 2). The partial correlation coefficient of NPP with NDVI, slope, precipitation, ETo, temperature, RVI, TP, and TN was 0.303, 0.265, 0.499, 0.459, −0.348, −0.134, −0.145, and 0.13, respectively. The degree of partial correlation was relatively large, confirming that these were the main factors affecting the productivity of cultivated land in SRB.

Multiple regression analysis revealed that the model of factors impacting CLP was:

$$Y_{NPP} = 0.494X_{NDVI} + 0.195X_{Slope} + 0.489X_P + 0.391X_{ETo} - 0.291X_{Temp} - 0.207X_{RVI} - 0.141X_{TP} + 0.125X_{TN}$$

The goodness-of-fit test results for the model were: correlation coefficient R = 0.742, determination coefficient R^2 = 0.550. Checks

TABLE 2 Path analysis and regression analysis of the relevant parameters to extracting factors

Model	Unstandardized coefficients B	Unstandardized coefficients SE	Standardized coefficients	*T*	Sig.	Partial correlations
(Constant)	−286.191	18.315		−15.626	0.00	
NDVI	457.5	25.63	0.494	17.85	0.00	0.303
Slope	7.001	0.453	0.195	15.442	0.00	0.265
Precipitation	0.196	0.006	0.489	32.318	0.00	0.499
ETo	0.188	0.006	0.391	29.032	0.00	0.459
Temperature	−15.392	0.738	−0.291	−20.863	0.00	−0.348
RVI	−3.759	0.495	−0.207	−7.589	0.00	−0.134
TP	−215.653	26.206	−0.141	−8.229	0.00	−0.145
TN	106.702	14.536	0.125	7.341	0.00	0.13

TABLE 3 Path analysis of the main factors

Main factors	Coefficients with NPP	Direct effects	Indirect effects X_{NDVI}	X_{Slope}	X_P	X_{ETo}	X_{Temp}	X_{RVI}	X_{TP}	X_{TN}	Synergistic effects 1
X_{NDVI}	0.484	0.494		0.012	0.166	−0.076	0.078	−0.186	−0.032	0.028	−0.010
X_{Slope}	0.338	0.195	0.029		0.105	−0.042	0.045	−0.011	0.001	0.015	0.143
X_P	0.435	0.489	0.168	0.042		−0.158	−0.048	−0.069	0.003	0.009	−0.053
X_{ETo}	0.061	0.391	−0.096	−0.021	−0.198		−0.044	0.037	0.005	−0.013	−0.330
X_{Temp}	−0.26	−0.291	−0.132	−0.030	0.080	0.059		0.048	0.038	−0.033	0.030
X_{RVI}	0.4	−0.207	0.443	0.010	0.164	−0.070	0.068		−0.032	0.025	0.607
X_{TP}	0.059	−0.141	0.111	−0.002	−0.012	−0.014	0.077	−0.047		0.087	0.200
X_{TN}	0.196	0.125	0.112	0.024	0.037	−0.041	0.077	−0.041	−0.098		0.070

on the independence of residuals using the Durbin-Watson test showed that its parameter DW = 2.067 fulfilled requirements (Table S4), indicating that the residuals were normally distributed, and the equations were significant. The p value for each influencing factor was <0.05, so all were significant (Table 2).

The direct influence of main factors on CLP was called the 'single effect' of these factors. The single effect of NDVI on CLP was 0.494, which was the largest impact intensity. The effect intensity of precipitation, ETo, temperature, RVI, slope, TP, and TN on CLP was 0.489, 0.391, 0.291, 0.207, 0.195, 0141, and 0.125, respectively. The single effect of NDVI, precipitation, ETo, Slope and TN on CLP was positive, while the single effect of temperature, RVI, and TP on CLP was negative.

3.4 | Intensity and direction of synergies among factors on CLP

3.4.1 | Intensity and direction of synergies among main factors on CLP

Path analysis showed that the synergistic effect between each main factor and RVI on CLP was the strongest synergistic effect (0.607) (Table 3). The synergistic effect of each main factor with ETo, TP, slope, TN, precipitation, and temperature on CLP declined in that order, with a value of 0.330, 0.200, 0.143, 0.070, 0.053, and 0.030, respectively. The synergistic effect of each main factor and NDVI on CLP was lowest (0.010). The synergy of the main factors with ETo, precipitation, NDVI had a negative impact on CLP, while the synergy of the other main factors had a positive impact.

3.4.2 | Intensity and direction of synergistic effects between other factors and main factors on CLP

Cluster analysis showed that there were synergies among the factors influencing CLP. Based on a distance of 20 between groups, the impact factors fell into nine groups (Figure S11). In terms of the synergy between other factors and the main factors, there were five groups, comprising: NDVI, RVI, and precipitation; slope, and DEM; ETo and sunshine duration (Sun); temperature and DVI; and TN, TP, total potassium (TK), and organic content (OC). Complete quadratic regression analysis was used to assess the synergy between the factors. The influence intensity and direction of other factors on the main factors were mainly determined according to the coefficients of the primary factor in the regression equation (Table 4).

TABLE 4 Path analysis and regression analysis between the main factors and other influencing factors

Main factors	Other factors	Regression equation	Synergistic effects 2
NDVI	Precipitation RVI	$X_{NDVI} = 0.044X_P + 0.883X_{RVI}$ ($R = 0.898$, $R^2 = 0.807$)	0.412
Slope	DEM	$X_{Slope} = -0.535 + 0.007X_{DEM} + 1.319 \times 10^{-5}X_{DEM}^2 - 1.5 \times 10^{-8}X_{DEM}^3$ ($R^2 = 0.304$, $p < 0.01$)	0.051
ETo	Sun	$X_{ETo} = 0.396X_{Sun}$ ($R = 0.396$, $R^2 = 0.157$)	−0.159
Temperature	DVI	$X_{Temp} = 0.453X_{DVI}$ ($R = 0.453$, $R^2 = 0.205$)	0.07
TN	TP TK OC	$X_{TN} = 0.581X_{TP} + 0.347X_{OC} - 0.045X_{TK}$ ($R = 0.763$, $R^2 = 0.582$)	0.026

The interaction between the main factors and other influencing factors and the synergistic effect of the main factors on CLP through the other factors were as follows (Table 4). Among the main factors affecting CLP in the first group (NDVI, RVI, precipitation), RVI and precipitation had positive effects on NDVI, but NDVI was mainly affected by RVI (influence intensity 0.883) and precipitation had little effect (intensity only 0.044). However, NDVI had a positive synergistic effect on CLP through RVI and precipitation (intensity 0.412).

In the second group, DEM and slope had a nonlinear relationship. DEM had little influence on slope (intensity 0.007) and slope had a positive synergistic effect on CLP through DEM (intensity 0.051).

In the third group, the relationship between Sun and ETo was positive. When Sun increased by 1%, ETo also increased by 0.396% in the same direction. However, ETo had a negative synergistic effect on CLP through Sun (intensity 0.159).

In the fourth group, DVI and temperature were positively related, such that if DVI increased by 1 unit, then temperature increased by 0.453 units in the same direction. However, temperature had a positive synergistic effect on CLP through DVI (intensity 0.07).

In the fifth group, TP and OC had a positive effect on TN (intensity 0.581 and 0.347, respectively). TK had a negative impact on TN (intensity 0.045). In addition, TN had a positive synergistic effect on CLP through TP, TK, OC (intensity only 0.026).

3.5 | Comprehensive analysis of the single and synergistic effects of influencing factors on CLP

The factors influencing CLP were closely linked and interacted, but the magnitude, intensity and direction of the synergistic effects among the factors differed. NDVI, slope, precipitation, ETo, temperature, RVI, TP, and TN were the factors with the most significant impact on CLP. For example, NDVI and precipitation had the greatest positive effects on CLP, 0.494 and 0.489 respectively while temperature had the greatest negative effect, 0.291. The single effect of the main factors, the synergies among the main factors, and the synergy between the main factors and other factors affected CLP to different degrees and in different directions. For example, the synergistic effect between each main factor and RVI on CLP was the strongest synergistic effect (0.607), while the negative synergistic effect of each main factor and NDVI on CLP was lowest (0.010). Overall, the single effects of the main factors and the synergy between the factors had important impacts on CLP in the study area (Figure 6).

4 | DISCUSSION

4.1 | Impact of the changes in cultivated land area and NPP on CLP

The cultivated land resource is the most important means of agricultural production and one of the most basic national strategic resources (Wu et al., 2017). We found that the area of cultivated land in the SRB changed frequently (Figure 3), which affected the spatial patterns and magnitude of soil erosion, affecting land productivity (Borrelli et al., 2017). At the same time, abandoning poor cultivation land and occupying new land for farming will cause the quality of soil to decline, and CLP will run a risk of declining (Liu et al., 2017). Land occupation for cultivation is the main driving force in soil degradation according to trajectory analysis (Yan, 2020). If not cultivated, most new land is expected to be suitable for grassland and forestry (Lindborg et al., 2013).

At present, the productivity of cultivated land is increasing over time (Figure 5). This is because China is increasing crop production mainly through increased use of fertilizers and pesticides (Zhuang et al., 2019). In the short term, the productivity of cultivated land has been dramatically improved. In the long run, there is still a potential risk of decline in CLP, mainly due to long-term application of fertilizers and pesticides causing soil hardening and salinization (Bi et al., 2017). Therefore, the productivity of cultivated land should not be measured solely based on the actual output while ignoring protection of local factors that affect CLP.

From a spatial point of view, NPP differs between regions due to the limitations imposed by the main influencing factors (Figure 4). Different levels of productivity exist, but places with low productivity will lead to a vicious circle of land occupation—ecosystem deterioration—further land occupation (Yang et al., 2019). Therefore, improving the productivity of cultivated land in areas with low productivity is

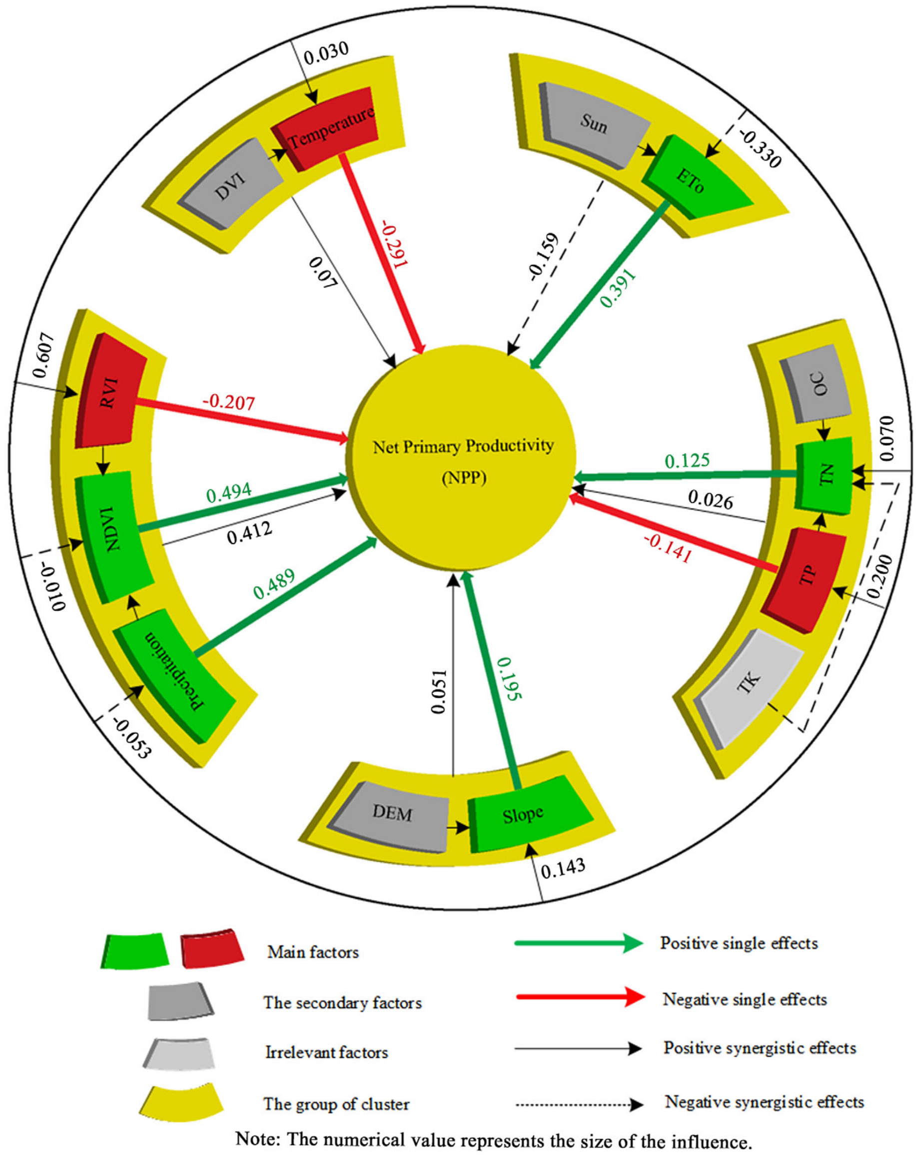

FIGURE 6 Influence of single and synergic factors on cultivated land productivity (CLP) in Songhua River basin [Colour figure can be viewed at wileyonlinelibrary.com]

essential not only for grain yield, but also for sustainable ecological security, as it will minimize expansion and prevent encroachment of agriculture onto other land types. In general, although unsustainable production methods will increase productivity, in the long run there is a risk that the quality of cultivated land will decline. Thus, regional and local governments should not consider only the short-term interests and ignore the potential long-term threats.

4.2 | Spatial heterogeneity of driving factors for CLP

Net primary production is the result of the long-term interaction and influence of nature, ecology, climate, and human activities, with significant effects of the main influencing factors on CLP (Mahé & Paturel, 2009). In particular, natural and ecological factors play a major role in CLP and socio-economic factors have less effect. In SRB, we found that the productivity of cultivated land was low in the middle of the basin and high in the surrounding area, indicating great heterogeneity (Figure 4). The eight main influencing factors and their synergistic effects resulted in spatial and temporal differentiation of CLP in the basin (Table 2).

Total nitrogen was a main influencing factor, and TK had a synergistic effect on TN (Table 2). Thus, interactions among the different influencing factors made a net positive contribution to CLP (Oehri et al., 2020). The accumulation rate of organic matter in the middle of the SRB was less than in the periphery, making a great contribution to NPP (Figure 4). The productivity of cultivated land was greatly affected by NDVI and RVI, in a positive and negative way, respectively (Figure 6). This confirmed that 'cultivated land' can be very different in terms of suitability and productivity for different vegetation types (Popp et al., 2016). In areas with more vegetative cover, NPP values were higher, meaning higher productivity in these areas (Wang et al., 2016). NDVI would also promote productivity in the process of vegetation restoration with the synergistic effect of soil quality improvement. This also verified that vegetation cover and restoration could improve the CLP (Quanhou et al., 2008). However, the negative synergy of factors, such as illumination being too long and an excess of evapotranspiration affecting crops, will lead to the reduction of crop yield (Table 4). We should also recognize the potential threat of negative synergy effects. We also found greater agricultural productivity in higher rainfall areas, and lower productivity in low rainfall zones (Figure S5), showing that CLP is also affected by precipitation (Table 3). Precipitation can cause relatively nutrient-rich soil to play a more significant role (Cohn et al., 2013), enabling high productivity. Therefore, the relative importance of soil feedback, their synergy, environmental dependence, and its impact on coexistence were noted (Lekberg et al., 2018).

The relationship between grain yield and phosphorus absorption showed a parabolic trend, first increasing and then decreasing, with the increase of phosphorus application (Ji et al., 2021). The world inputs 14.2 million tons of fertilizer phosphorus and 9.6 million tons of organic fertilizer phosphorus into the soil every year, and only 12.3 million tons of phosphorus is absorbed by crops, resulting in a significant increase in phosphorus in most cultivated land (MacDonald et al., 2011). The application of phosphorus fertilizer plays a positive role in improving crop yield, but when the phosphorus application rate increases to a certain extent, the yield starts to decrease (Gong et al., 2011; Ma et al., 2005). It is able to meet crop demand for phosphorus nutrition in SRB (Zhang, Du, et al., 2020), and we found that the percentage content of phosphorus was significantly higher than that of nitrogen in the regional location of cultivated land (Figure S12); this was also proved in the study of a dry farming area in Northeast China (Zhuo et al., 2019). Due to the slow fertilizer effect of phosphorus fertilizer and great after effects, the higher the amount of phosphorus application, the longer the cumulative life, and the higher the soil phosphorus surplus (Muller et al., 2017; Sattari et al., 2014). This would then start to limit growth after reaching the maximum threshold, and the total phosphorus would have a negative impact on CLP (Figure 6). This also strongly verifies that the content of soil available phosphorus in China has reached the level of no phosphorus deficiency, and the soil phosphorus pool in some high agricultural producing areas is at a surplus (Li et al., 2013). Now, the annual accumulation of soil phosphorus exceeds 90 kg hm^{-2} (Zhang et al., 2019).

4.3 | Collaborative management implications of cultivated land protection

The turbulence of international trade will place pressure on the food supply in China for a long time (El Bilali, 2020). To ensure future food security, cultivated land needs to be protected in a long-term plan. Without stable CLP, there can be no real food security (Feng & Li, 2000).

The first step should be rational allocation of cultivated land resources, planned implementation of land development (Xu et al., 2010), farmland expansion, consolidation and fallow rotation (Yu-sen, 2002), in strict accordance with the Chinese red line for cultivated land protection and the ecological red line (Bai et al., 2021). At the same time, regions with weak CLP identified in the spatiotemporal pattern of CLP should be supported. Integrated soil conservation measures on cultivated land need to be implemented, such as prevention of soil erosion (Guerra et al., 2020), desertification (Briassoulis, 2019; Siqueira-Gay et al., 2020), salinization and poor cultivation practices (Cuevas et al., 2019).

Second, the impact of a single factor or multi-factor coupling on CLP in different development stages may change (Table 3 and 4). We should pay attention to the threshold of collaborative management on the influencing factors of CLP, so that the relevant factors are in a dynamic collaborative state. The research showed that the ecological threshold of soil available phosphorus was 25 mg kg^{-1}, which not only met the high yield of crops but also did no harm to the ecological and environment (Zhang, Huang, et al., 2020). We should look for appropriate phosphorus reduction measures. There are differences in the phosphorus content of topsoil in different regions. During the process of phosphorus fertilizer application, we need to make corresponding adjustments according to local conditions. This can not only realize efficient land use with a dynamic balance of influencing factors of cultivated land resources as the core but also maintain the utilization rate of phosphorus fertilizer at a high level, reduce the accumulation of phosphorus in soil and reduce environmental risks. Overall, protection of cultivated land in the future should include clearer land use regulation, the promotion of productivity factors at different spatial scales and the interaction among factors.

4.4 | Innovation and limitations

This study identified the following innovations: (1) Analysis of factors influencing CLP can be based on the specific relationship with NPP, which can be used for accurate calculation of the relationship between CLP and influencing factors at grid scale. This overcomes the drawback associated with using statistical yearbook data on food output at the scale of administrative divisions in factor analysis of CLP, where the results are too 'macro'. Thus for large-scale watersheds, the accuracy of calculation is improved. (2) Analysis of the factors influencing CLP combined with analysis of synergistic effects of the main factors and other factors provides powerful support in formulation of policies for the protection of cultivated land. (3) Analysis at the large watershed scale increases the general applicability of the findings compared with previous experimental tests based on a small watershed or research area, and the findings have high relevance for similar large river basins elsewhere in the world.

However, there were also some limitations. Due to the large spatial scope of the river basin studied, the quality of data on the influencing factors was low and expression ability in regression analysis was lacking. For future research, there is a need for better data acquisition methods to improve the quality of the scientific data.

5 | CONCLUSIONS

The following conclusions were drawn: (1) NPP can reflect the CLP level in each grid and can effectively construct the relationship between the factors affecting CLP. The productivity of cultivated land shows great heterogeneity which is mainly characterized by low central productivity and high surrounding productivity, increasing year by year over time, with eight main influencing factors and their synergistic effects causing spatial and temporal differentiation in CLP. (2) The factors influencing CLP are closely related and interact with each other, but the magnitude, intensity, and direction of synergies among the factors differ. In particular, TN is one of the main positive factors, while TP may have reached the highest threshold content for the soil, showing a negative impact. The strongest positive synergistic effect of each main factor and RVI on CLP was 0.607, and the strongest negative synergistic effect with ET_O on CLP was 0.330. The degree of impact on CLP in the SRB also varied. (3) Synergies among the eight main factors greatly impact the productivity of cultivated land. Specifically, NDVI and precipitation had the greatest positive effects on CLP, 0.494 and 0.489 respectively while temperature had the greatest negative effect, 0.291. The single effects of the main factors and the synergistic effects of factors have an important impact on CLP in the study area. We learned that the synergistic effect between each main factor and RVI on CLP was the strongest synergistic effect (0.607). All in all, the impact of the main factors on CLP helps us to better protect cultivated land according to local conditions, and the synergistic effect of various factors helps us to better manage the matching of suitable soil elements.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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