Estimation of maize yield incorporating the synergistic effect of climatic and land use change: A case study of Jilin, China

Xinyuan wen[1,1,1,1], Dianfeng Liu[1,1,1,1], Mingli Qiu[1,1,1,1], and Yinjie Wang[1,1,1,1]

[1]Wuhan University

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Abstract

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Xinyuan Wen[1], Dianfeng Liu[1,2*], Mingli Qiu[1], Yinjie Wang[1] and Jiqiang Niu[3]

[1] School of Resources and Environmental Sciences, Wuhan University, Wuhan, PR China.

[2] Key Laboratory of Digital Cartography and Land Information Application Engineering, Ministry of Natural Resources, Wuhan, PR China.

[3]Key Laboratory for Synergistic Prevention of Water and Soil Environmental Pollution, Xinyang Normal University, Xinyang, PR China.

*Corresponding author: Dianfeng Liu (liudianfeng@whu.edu.cn)

Abstract

Yield forecasting can give early warning of food risks and provide theoretical support for food security planning. Climate change and land use change directly influence the regional yield and planting area of maize, but few existing studies have examined their synergistic impact on maize production. In this study, we combine system dynamic (SD), the future land use simulation (FLUS) and a statistical crop model to predict future maize yield variation in response to climate change and land use change. Specifically, SD predicts the future land use demand, FLUS simulates future spatial land use patterns, and a statistical maize yield model based on regression analysis is utilized to adjust the per hectare maize yield under four representative concentration pathways (RCPs). A phaeozem region in central Jilin Province of China is taken as a case study. The results show that the future land use pattern will significantly change from 2030 to 2050. Although the cultivated land is likely to reduce by 862.84 km^2, the total maize yield in 2050 will increase under all four RCP scenarios due to the promotion of per hectare maize yield. RCP4.5 will be more beneficial to maize production than other scenarios, with a doubled total yield in 2050. Notably, the yield gap between different counties will be further widened, which necessitates the differentiated policies of agricultural production and farmland protection, e.g., strengthening cultivated land protection and crop management in low-yield areas, as well as taking adaptation and mitigation measures to coordinate climate change and crop production.

Keywords

Maize yield forecast; land use simulation; RCP scenarios; models

1 Introduction

Agriculture plays a vital role in food security, poverty elimination and sustainable development (Loboguerrero et al., 2019). With the remarkable growth of the global population, agricultural production has faced a significant challenge in meeting the increasing food demand and varying diet structure of human beings. Moreover, farmland loss and degradation caused by urban expansion and economic development have exacerbated this situation (Vermeulen et al., 2012). In this context, forecasting food production can give an early warning of food risk and support agricultural land use activities and the corresponding policy making([Preprint] Wen et al., 2022).

The existing yield prediction methods can be categorized into statistical models and process-based models. The traditional statistical models have been commonly employed to forecast seasonal variations of crop yield, e.g., linear and non-linear regression analysis and their integration with principal component analysis. Currently, machine learning approaches, e.g., random forest (Sakamoto, 2020), XGBoost, long-short-term memory (LSTM), and convolutional neural network (CNN), have received more and more attention due to their ability to describe complicated relationships of crop production and the driving forces (Hengl et al., 2017; Kang et al., 2020; Leng and Hall, 2020; Poornima and Pushpalatha, 2019; Yang et al., 2019; Zhong et al., 2019). These statistical models can relate historical yield data with the agrometeorological variables, for example, march temperature difference, daily relative humidity changes, sunshine hours, and the remote sensing-based variables (Banakara et al., 2019; Camberlin and Diop, 1999; Giri et al., 2017; Sharma et al., 2017), such as Normalized Difference Vegetation Index (Peralta et al., 2016), Vegetation Condition Index (Kowalik et al., 2014), and Vegetation Health Index (Wang et al., 2010).

Process-based crop models employ integrated mathematical methods to describe crop growth status driven by climate, nutrient and water cycling, soil properties and agricultural management practices (Basso et al., 2016). This type of models includes CERES-Millet, EARS-CGS, PUTU, WOFOST and SWAP (Manatsa et al., 2011**;** Roebeling et al., 2004**;** Rojas, 2007**;** Tripathy et al., 2013), which have been applied to maize, wheat, barley, and millet prediction. Although these models have been proven efficient in practice, they still suffer from significant uncertainties because of complex parameters calibration and initialization (Kolotii et al., 2015).

For example, a number of these models will be calibrated using genetic information of plants that is hardly quantified. In contrast, statistical models allow us to capture essential processes that may be overlooked in the process model, including the impact of extreme temperatures on canopy transpiration and photosynthesis and the damage to crops caused by weather, pests, and diseases (Urban et al., 2012). Therefore, this study adjusted a statistical model to predict maize yield per hectare instead of a process-based crop model.

Climate and land use change have been regarded as two worldwide influencing factors of maize production (Basso and Liu, 2019). Climate change affects crop growth by changing temperature, precipitation, CO_2, nitrogen, and other critical ecological factors, during the growing season. Land use change analysis can improve yield forecasts' accuracy by identifying the chop's changed planting areas (Vancutsem et al., 2013). However, a better understanding of the synergistic effect of climate change and land use change on maize yield in a spatially explicit way is still lacking at present. Combining statistical models and spatial land use simulation models have been proven promising to address this issue. Land use simulation approaches originated from cellular automata enable us to project changes in quantity and spatial pattern of agricultural land, and incorporate the effect of land use change into the crop yield estimation (Akpoti et al., 2019; Liu et al., 2017). Moreover, these simulation models can be equipped with various complex approaches, e.g., neural network, multi-agent system, and multinomial logistic regression, to pursue better simulation performance (Basse et al., 2014; Mustafa et al., 2018; Yeldan et al., 2012). Due to the flexible model framework, numerous driving factors can also be incorporated into maize yields, like urbanization, agricultural machinery advancement, and population economic growth, etc. (Abate and Kuang, 2021; Takeshima et al., 2013; Yu et al., 2020; Zhang et al., 2017b).

We demonstrated a new crop prediction framework based on the integration of a statistical crop yield approach and a spatial land use simulation model, and examined the synergistic effects of climate change and land use change on maize yields. Further, we designed four future scenarios based on representative concentration paths (RCPs) to examine the direct effects of climate change and socio-economic development on maize yield per hectare. We conducted a case study in the phaeozem region of central Jilin Province, China, and validated the proposed model. Our work is expected to provide a generic framework for the spatially explicit forecast of maize yield.

2 Materials and Methods

2.1 Study area

A phaeozem region in central Jilin Province of China was selected as the study area, consisting of Changchun, Jilin, Siping, Liaoyuan, and Tonghua City (**Figure 1**). This region is located in the major golden maize belts across the world, and plays an irreplaceable role in national food security as one of the primary grain production bases and commodity grain export bases in China (Asseng et al., 2013; Li et al., 2020). The rain-fed maize system was selected as the research object to eliminate the effect of irrigation on crop yield (Urban et al., 2012).

The region features a short growing season of maize from May to September (Feng et al., 2021; Jiang et al., 2021; Yang et al., 2007). Over the past 50 years, the average annual temperature has increased significantly by 0.38°C per decade, precipitation has decreased slightly, and droughts and floods have become more frequent (Liu et al., 2009; Yin et al., 2016). Climate change will directly affect maize production. Existing studies have also shown that climate change has an indirect impact on land use (Pan et al., 2020; Yang et al., 2020). Therefore, it is necessary to assess the future impact of climate change and land use change on maize yields to support the decision-making of agricultural production.

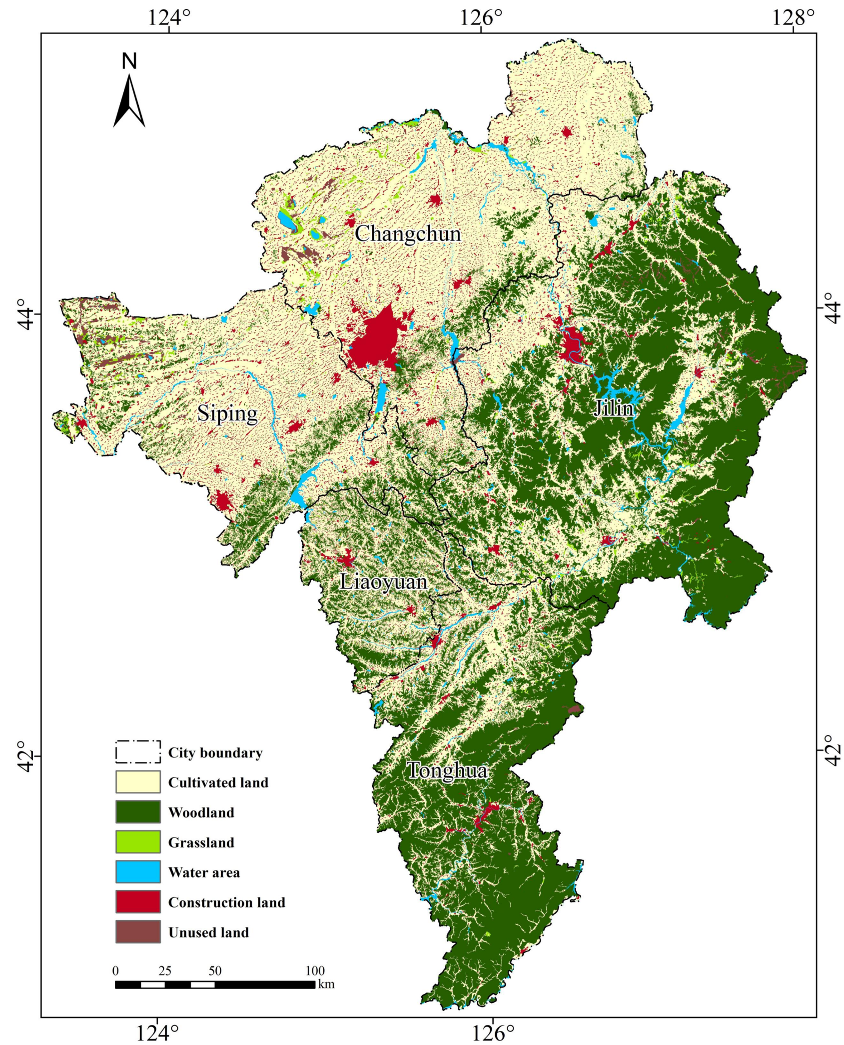

Figure 1. Location of the Study Area (background: empirical land use map in 2015).

2.2 Data source

The data collected in this study includes climate data, land use maps, socio-economic data and geographical information. Future climate data, i.e., precipitation and surface temperatures, were collected from WDCC (https://doi.org/10.1594/WDCC/ETHr2), which were generated using general circulation modelthe Beijing Climate Center Climate System Model version 1.1 m (BCC_CSM1.1 m)(Knutti, 2014). The data are at a T106 horizontal resolution (1.125°×1.125°) (Liu et al., 2021; Wu et al., 2010), and have been widely used to explore maize, wheat and other grain planting systems in northeast China (Gao et al., 2020; He et al., 2018; Jiang et al., 2021). Meanwhile, a time series of historical climate data was downloaded from the China Meteorological Data Network (http://data.cma.cn).

Empirical land use maps in 2000, 2005, 2010 and 2015 were derived from the Chinese Academy of Sciences (CAS; http://www.resdc.cn), categorized into six land use/cover types: cultivated land, woodland, grassland, construction land, unused land and water area(Ning et al., 2018). Socio-economic data, including urban/rural population, agriculture production, forestry, animal husbandry and fishery, were obtained from the Statistical Yearbook of Jilin Province (2000-2015). The raster datasets of population density and GDP(Xinliang, 2017a, b), and other geographic maps, including administrative boundaries, roads and railways, were derived from the Chinese Academy of Sciences database (http://www.resdc.cn/DOI). On the ArcGIS 10.5 platform, all spatial data were converted into raster maps at a spatial resolution of 30m. See **Table 1** for detailed data information.

Table 1

Research data and sources

Data	Data type	Temporal coverage	Source
Expenditure and production value of agriculture, forestry, animal husbandry and fishery	Excel	2000-2015	Jilin Province Statistical Yearbook
Total mechanical power, total grain production			
The proportion of urban population, total urban and rural population			
Science and technology expenditure			
County-level maize yield data			
Historical climate data	Excel	2000-2015	http ://data.cma.cn/
Annual average precipitation and annual average temperature	NetCDF	2006-2100	https://doi.org/10.1594/WDCC/ETHr2
Land use map	TIFF	2000-2015	http ://data.casearth.cn/
GDP spatial distribution		2000, 201	http ://www.resdc.cn
Spatial distribution of population density			

Digital Elevation Model (DEM)		5	/
Road network	shapefile		https ://www.openstreetmap.org/
Administrative boundary	shapefile	2015	http ://www.resdc.cn/

3 Methods

3.1 Integrated assessment framework

To examine the effect of climate change and land use changes on regional maize yield, we proposed an analytical framework based on the integration of system dynamics (SD), cellular automata (CA) and a statistical maize yield model (**Figure 2**). The SD projects land use demands from a top-down perspective based on socio-economic development and policy planning. The CA simulates spatial land use patterns from a bottom-up perspective. The integration of SD and CA enable us to predict land use changes in the study area from 2015 to 2050. Next, the statistical maize yield model was incorporated to predict maize yield per hectare under the impact of temperature, precipitation, agricultural technology and sunshine hours in four Representative Concentration Pathways (RCPs). Then, total maize yields under different scenarios were assessed based on the product of the simulated maize planting area and the predicted maize yield per hectare, and compared at two time periods of 2011-2030 and 2031-2050.

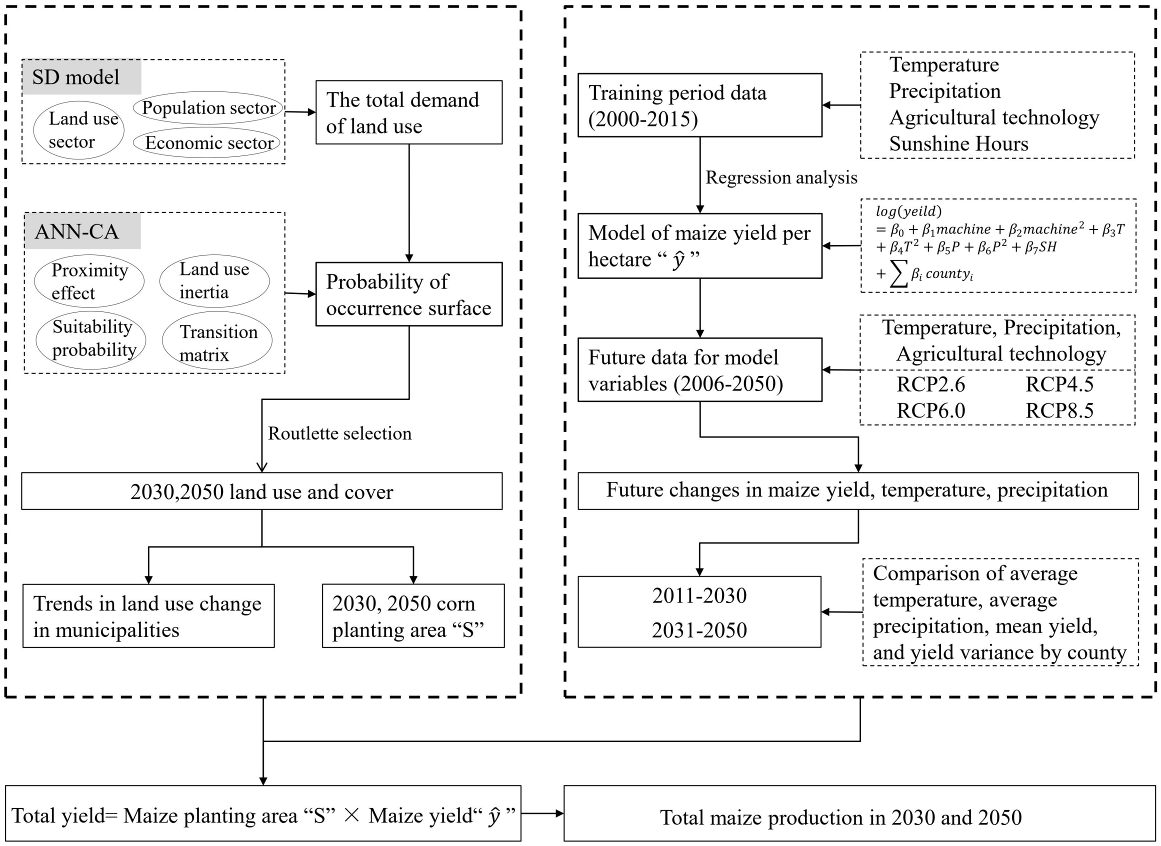

Figure 2. The analytical framework of future maize yield.

3.2 Future climate scenario design

Future scenarios are designed based on four RCP descriptions in CMIP5, a standard experiment protocol to define a series of coupled atmosphere-ocean general circulation models developed by Climate Modeling Groups, World Climate Research Project (WCRP), and International Geosphere-Biosphere Project (IGBP) (Kriegler et al., 2014; O'Neill et al., 2014; Pan et al., 2020; van Vuuren and Carter, 2014). The four RCPs reflect the radiative forcing levels of 2.6, 4.5, 6.0 and 8.5 W/m^2 by 2100. Each RCP pathway describes a range of climatic and socio-economic characteristics related to different levels of carbon emissions (van Vuuren and Carter, 2014), i.e., average temperature and precipitation in the growing season (**Figure A1**), and agricultural mechanization promotion (Rotz et al., 2019). Average temperature and precipitation under four RCPs were set according to historical and projected climate datasets. The growth rates of agricultural technology under four RCPs were determined to simulate the future maize yield based on the actual development of Jilin Province and previous research experience (**Table 2**).

Table 2

The growth rate of agriculture technology

Scenarios		Growth rate
RCP 2.6	Level	High
	Growth rate	+7%
RCP 4.5	Level	Relatively high
	Growth rate	+5%
RCP 6.0	Level	Moderate
	Growth rate	+3%
RCP 8.5	Level	Low
	Growth rate	0

3.3 Projection of future land use demand

The prediction of the planting area of maize consists of two steps: land use demand projection and spatial pattern allocation. In the first step, future land use demands were projected using the system dynamic (SD) model. The SD model enables us to simulate the complex evolution process of the land system through the feedback and interaction between different elements (Akhtar et al., 2013).

The SD model in this study comprises three sections: population, social economy, and land use (**Figure 3**). The population section represents urban and rural changes related to socio-economic development and land use demands for urban and rural settlements and agricultural production. The socio-economic section considers the effect of agricultural technology development and fixed asset investment change on agriculture, forestry, and fishing production. Further, the land use section illustrates land use conversions and their driving forces in terms of population, socio-economic development and interaction among various land use types (Liu et al., 2017). For example, cultivated land may expand due to a series of farmland supplementation measures, e.g., the consolidation of rural settlements and the reclamation of wild grassland, and will decline because of farmland reforestation and urban encroachment. The interaction and feedback among the three sections are defined through regression methods. The time range of the SD model in this study is from 2011 to 2050, and the time step is one year. Outputs of the SD were used to limit land use quantities in the spatial land use pattern allocation.

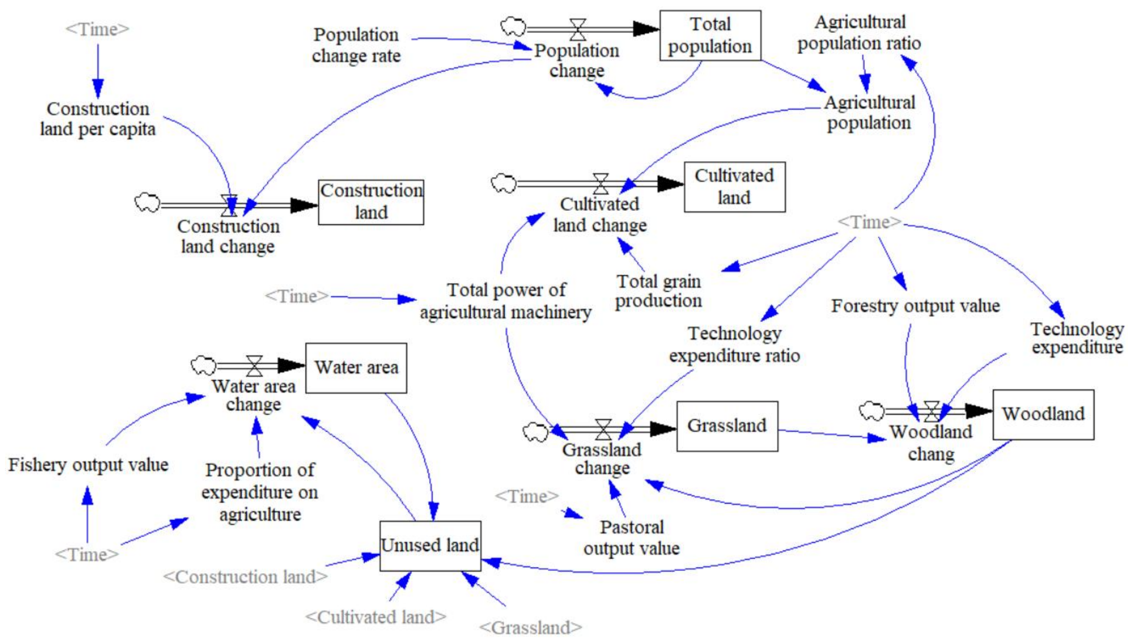

Figure 3. Interaction and feedback relationships in the system dynamic model.

3.4 Allocation of spatial land use pattern

The spatial pattern of land use was allocated using the FLUS model based on the land use demand from the SD. The FLUS consists of two modules (Liu et al., 2017): (1) estimating the occurrence probability of each land use type on a specific grid unit based on a three-layer artificial neural network (ANN); (2) determining the land use type of each grid cell based on the cellular automata (CA) approach. Specifically, the three-layer ANN was trained using the empirical land use data and various driving factors that combine socio-economic and natural effects, including population density, GDP, elevation, slope, aspect, distance to main highways, distance to primary railways, distance to rivers, and distance to cities (Yang et al., 2020). The CA calculates the combined probability of a specific land use type on each grid cell based on the product of the occurrence probability, land use conversion cost, spatial neighborhood effect and land use inertia coefficient (Li et al., 2017), and then allocates the suitable land use type to each grid cell using the roulette selection method (Pan et al., 2020). See Yang et al. (2020) for detailed model descriptions and parameterizations.

3.5 Estimation of maize yield per hector

Maize yield per hector was estimated using a regression analysis based on the historical data of maize production from 2000 to 2015. A series of essential factors for photosynthesis and plant growth in terms of county-level differences, socio-economic development and physical conditions were selected as independent variables, including the mean and variance of temperature and precipitation in the growing season(Lobell et al., 2011; Urban et al., 2012), the total power of agricultural machinery, and sunshine hours (Murchie and Niyogi, 2011). Considering the non-linear relationship between climate variables and maize yields and moderately/strongly skewed distribution of maize yields (Huang et al., 2021), the logarithm of the maize yield rather than the yield *per se* was used as the dependent variable. Moreover, the quadratic function has been proved promising in simulating the dynamic relationship between climate conditions and maize yield (Grassini et al., 2009; Lobell and Burke, 2010).

The regression model for the estimation of per unit maize yield can be expressed as follows:

$$log\,(\hat{y}) = \beta_0 + \beta_1 machine + \beta_2 machine^2 + \beta_3 T + \beta_4 T^2 + \beta_5 P + \beta_6 P^2 + \beta_7 SH + \sum \beta_i\, county_i \qquad (1)$$

where *T, P,* and *SH* represent the temperature, precipitation, and sunshine hours during the growing season from May to September. *county* is a dummy variable to capture the spatially heterogeneous influence of physical and socio-economic factors at the county level, such as soil quality and agronomic. $machine$ accounts for an improvement in agricultural mechanization. Square terms of independent variables denote a certain degree of nonlinearity (see **Text A1** and **Table A1** for detailed parameters).

Moreover, the average change of maize yield often accompanies its variance change. The variance of per hectare yield can measure the stability of the inter-annual production of maize, which is significant in maintaining the steady income of farmers and ensuring regional food security. The yield variance can be calculated in the following:

$$Var(y) = (E[\log(\hat{y})])^2 \times Var(\log(\epsilon)) + (E[\log(\epsilon)])^2 \times Var(\log(\hat{y})) + Var(\log(\hat{y})) \times Var(\log(\epsilon)) \qquad (2)$$

where $Var(y)$ refers to the variance of yield per hectare in each county, and ϵ refers to the residual yield per hectare.

We used the residuals of training data (**Table A2**) to calculate the expected $Var(y)$. Therefore, we assumed that the yield residual would not change with the change of predicted climate. To verify this hypothesis, we conducted least square regression between the yield residuals' square $[log(\epsilon)]^2$ and the average T and P in the training period. The results showed that climate change causes a slight change in $[log(\epsilon)]^2$ (**Figure A2**). Therefore, in this study, the assessment results of yield variation under future climate will be relatively conservative.

3.6 Model implementation and evaluation

The SD model was built with Vensim (https://vensim), and the FLUS was performed in the GEOSOS platform. The empirical land use data in 2000 and 2015 were used to train and validate the simulation model. Kappa coefficient was used to evaluate the accuracy of land use simulation. Overall, the average accuracy rate exceeds 80%, and the Kappa coefficient reaches 0.65, indicating the positive performance of the FLUS. Further, regression analysis was conducted in SPSS. The standardized residuals of the regression model obey the normal distribution, and R^2 equals 0.436. These experimental results indicate the good performance of the proposed framework for maize yield projections.

4 Results & discussion

4.1 Dynamic land use changes

The study area will experience slight changes in cultivated land and woodland, and remarkable changes in construction land, grassland, water areas and unused land by 2050. Land use changes will exhibit evident spatially differences across the study area (**Figure 4** and **Figure A3**). As for cultivated land, the total area will slightly increase from 43,321.70 km^2 in 2010 to 43,556.00 km^2 in 2050, with an inverted U-shaped trend. Specifically, the cultivated land will increase to 44,424.08 km^2 in 2030 and then drop by 867.61 km^2 from 2030 to 2050. However, the trend will differ from at the city level. The cultivated land in Changchun and Liaoyuan will increase by 485.68 km^2 and 19.62 km^2 in 2010-2050, while those in Tonghua, Jilin and Siping will decrease by 252.12 km^2, 11.33 km^2, and 3.88 km^2.

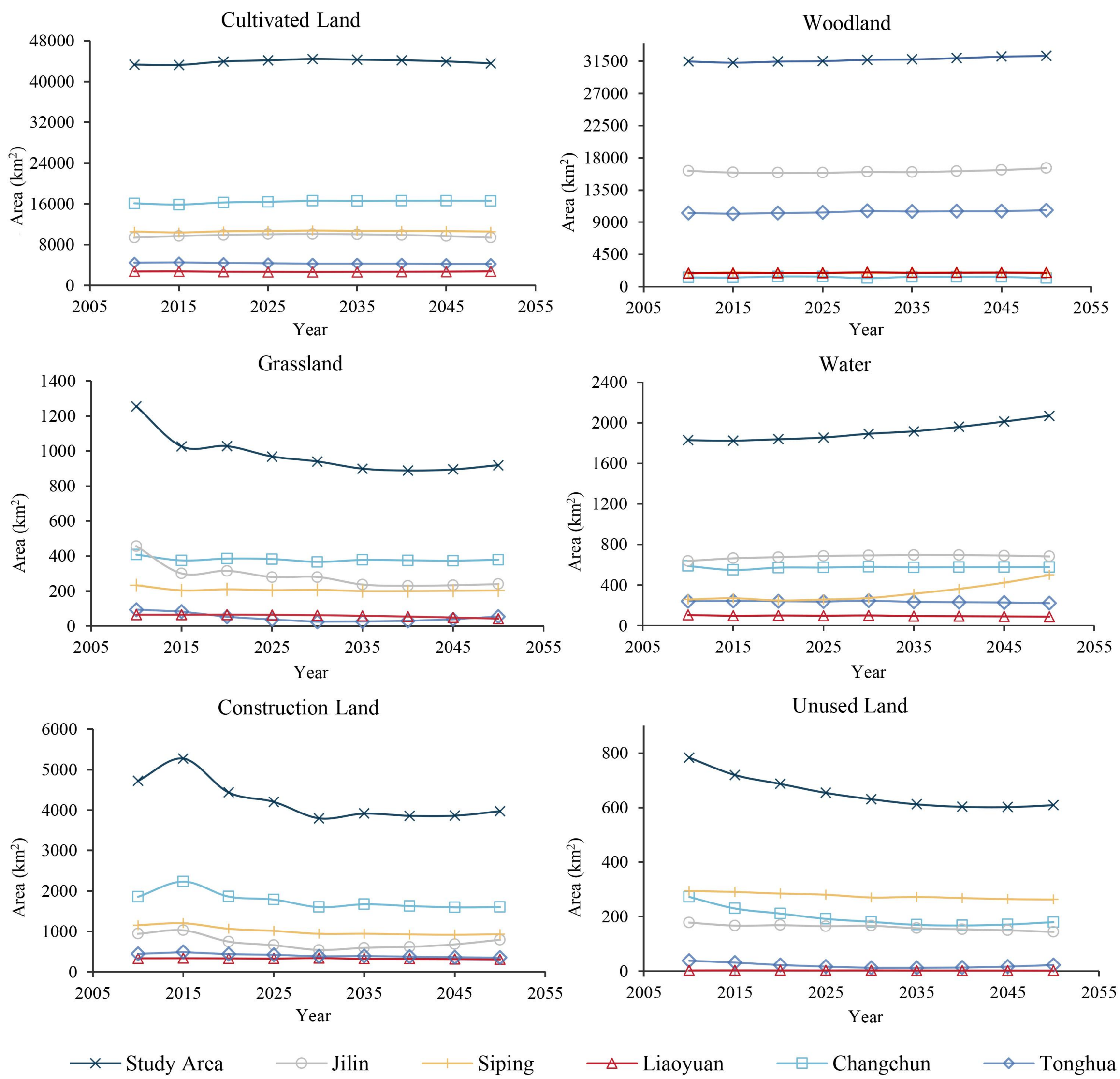

Figure 4. The changes in land use quantities from 2010 to 2050.

The gain and loss of cultivated land will be 3,796.69 km^2 and 3,561.53 km^2, respectively (**Figure 5f**). Specifically, 43.09% and 40.03% of farmland gain will be attributed to the reduction of woodland and construction land, for example, the consolidation of scattered rural settlements originating from rural population shrinkage (Liu et al., 2013b). In turn, 63.71% of farmland loss will be attributed to farmland reforestation, which indicates the Chinese government's emphasis on ecological protection (Shan et al., 2020). At the city level, Changchun has the highest farmland gain (**Figure 5a**). The gain of cultivated land will be 1,080.04 km^2, and 59.45% comes from the consolidation of construction land. As a central city in Northeast China, increasing cultivated land will alleviate the pressure of increasing population on food production (Zhang et al., 2012). Conversely, Tonghua has the largest reduction of arable land (**Figure 5e**). The gain and loss of cultivated land will be 471.00 km^2 and 722.52 km^2, respectively. It can be observed that 627.28 km^2 of cultivated land in this city will be converted into forest land. Liaoyuan, Siping and Jilin are likely to experience slight farmland gain or loss; these changes are less than 20 km^2 (**Figure 5b, c, and d**).

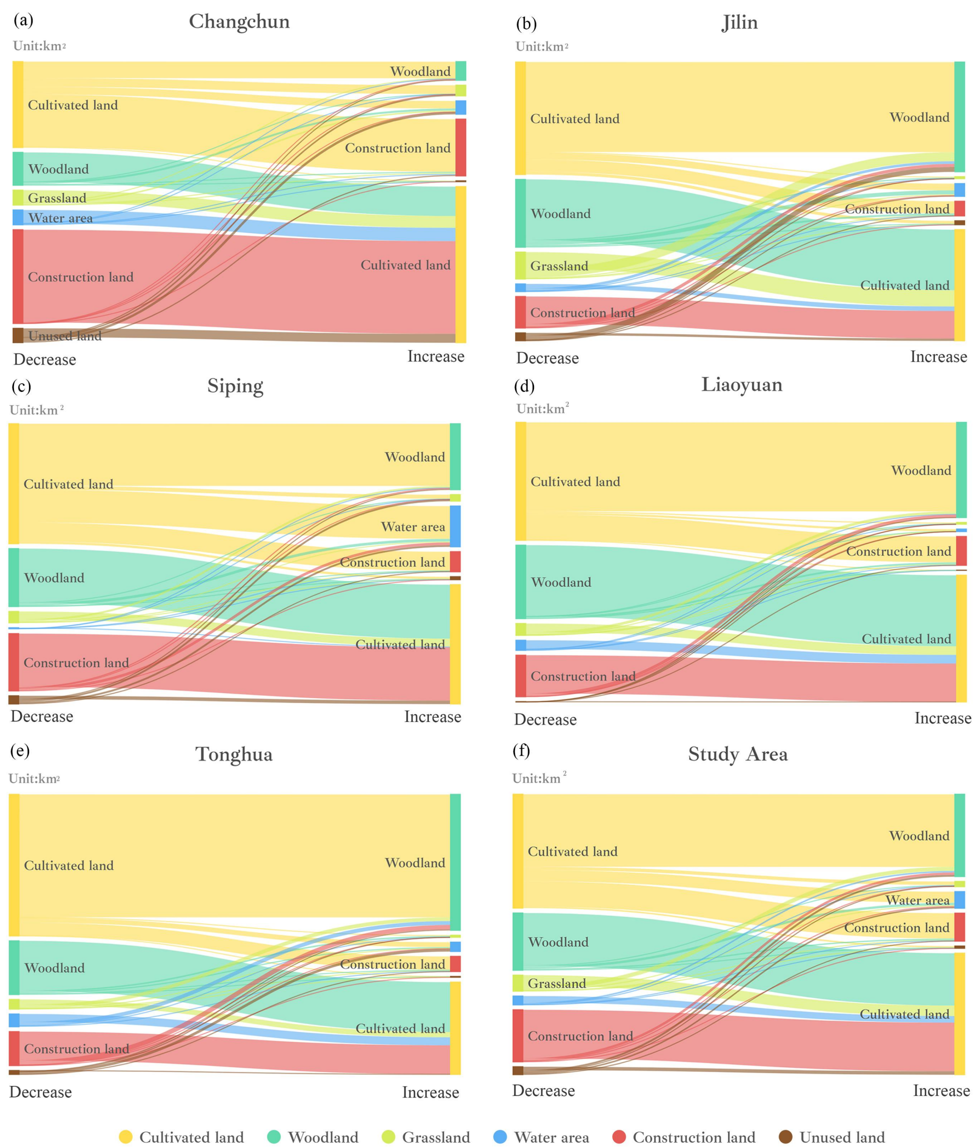

Figure 5. Land use conversions from 2010 to 2050.

4.2 Changes in maize yield per hectare in different scenarios

The maize yield per hectare is likely to exhibit a two-stage upward trend from 2011 to 2050 (**Figure 6**). From 2011 to 2030, it will moderately increase by 76.32%, 70.63%, 63.278%, 49.66% under RCP2.6, 4.5, 6.0, 8.5, respectively. From 2031 to 2050, however, it will experience a corresponding sharp promotion of 280.74%, 344.91%, 299.64%, and 233.352%.

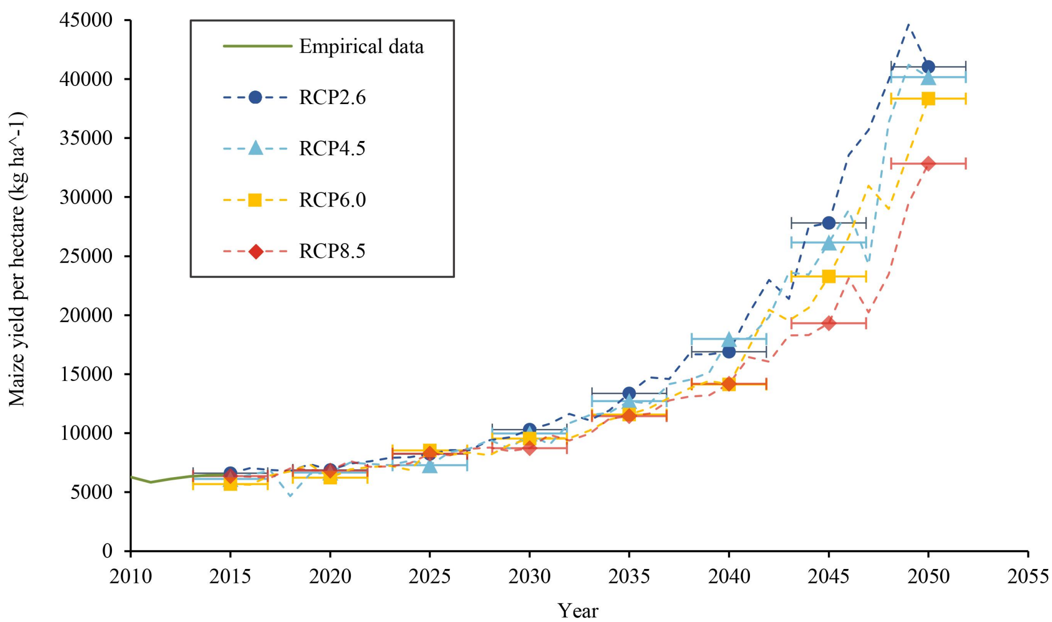

Figure 6. Changes in average maize yield per hectare under four RCP scenarios from 2011 to 2050. Standard Errors of Mean (SEM) of RCP 2.6, 4.5, 6.0, and 8.5 are 1575.51, 1401.41, 1252.26, and 975.38 *kg ha^-1*, respectively.

Climate change (**Figure A4)** may exert different effects on per unit maize yield over time. RCP 2.6 will have the maximum annual growth rate of the per-unit yield up to 34.73%, with a mean value of 14175.00 *kg ha^-1*. Conversely, RCP 8.5 is likely to exhibit the minimum increase of the per-unit yield by 11324.47 *kg ha^-1* with an annual growth rate of 33.78%. A positive correlation between the per-unit yield promotion and the radiative forcing levels caused by greenhouse gas emissions can be observed, and a growing gap in the per unit yields under four RCP scenarios will also arise over time. We further found that temperature strongly correlates with the changing rate of the maize yield variance (**Figure 7**). In RCP2.6, RCP6.0, RCP8.5, R^2 can reach up to 0.99 ($p<0.0001$), while that in RCP4.5 is only 47.21%. The temperature changes primarily lead to yield variance.

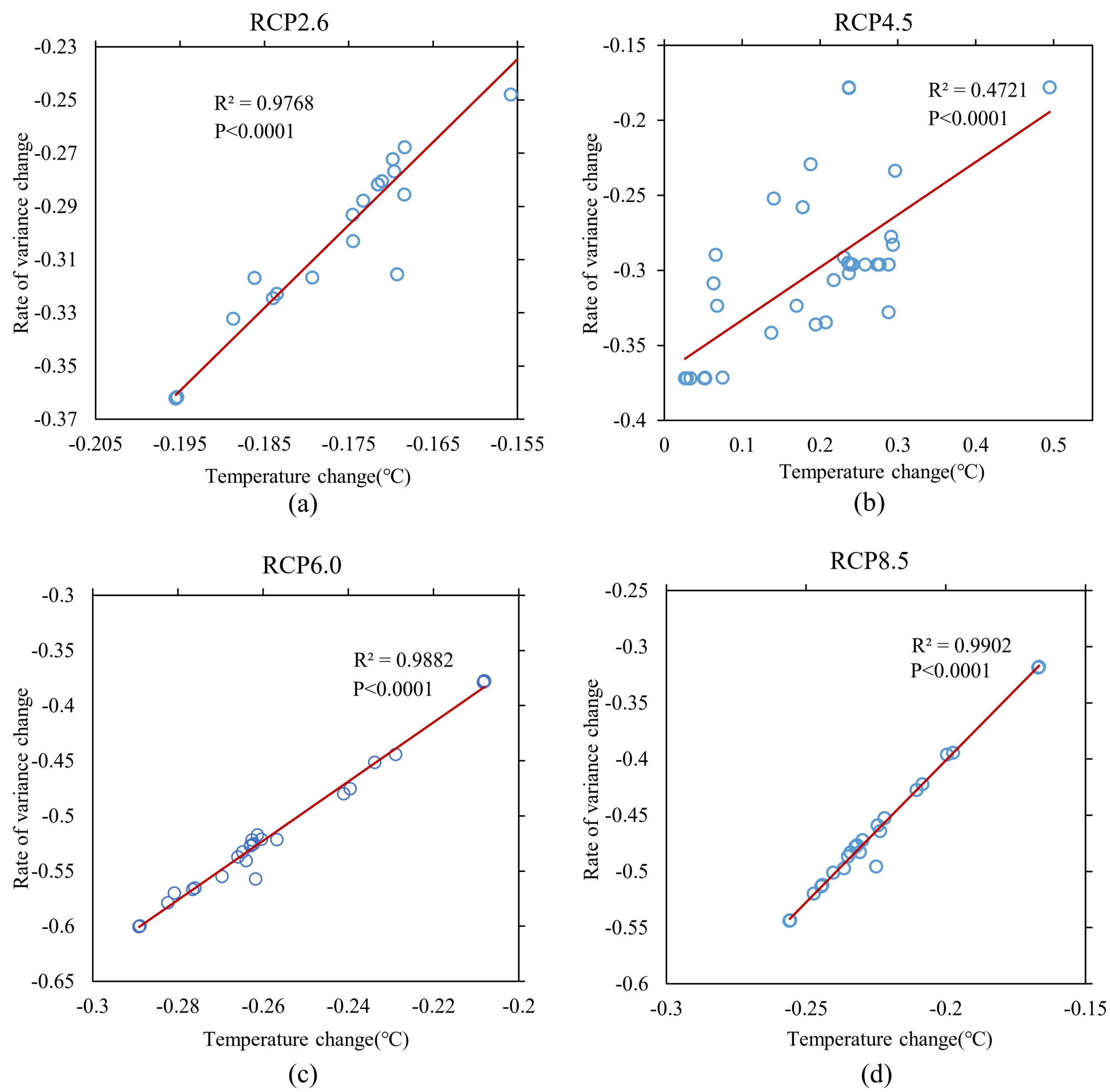

Figure7. Correlation analysis between temperature and variance transformation rate under four RCP scenarios.

At the county level, the yield variations under the four RCPs range from 0.72 to 32.82 from 2011 to 2030, varying from 0.82 to 32.87 in 2031-2050. In contrast, the mean per unit yield gap in the four RCPs will be much greater from 2031 to 2050. For example, the range of RCP2.6 in 2031-2050 can expand to 10 times that in 2011-2030. Despite the different distribution of values, the mean yields still exhibit a positive correlation with the variances. The spatial distribution of relative change in the mean yield per hectare and its variance in these two periods are similar, with a significant increase in the northern and central regions and a slight increase or decrease in the western region. Most counties had a similar change rate of average yield under the four RCPs, but the gaps under RCP2.6 and RCP6.5 are much larger (**Figure 8a**). From the perspective of the distribution area, RCP6.5 and RCP8.5 have a greater relative reduction of variance from 2011-2030 to 2031-2050 (**Figure 8b**).

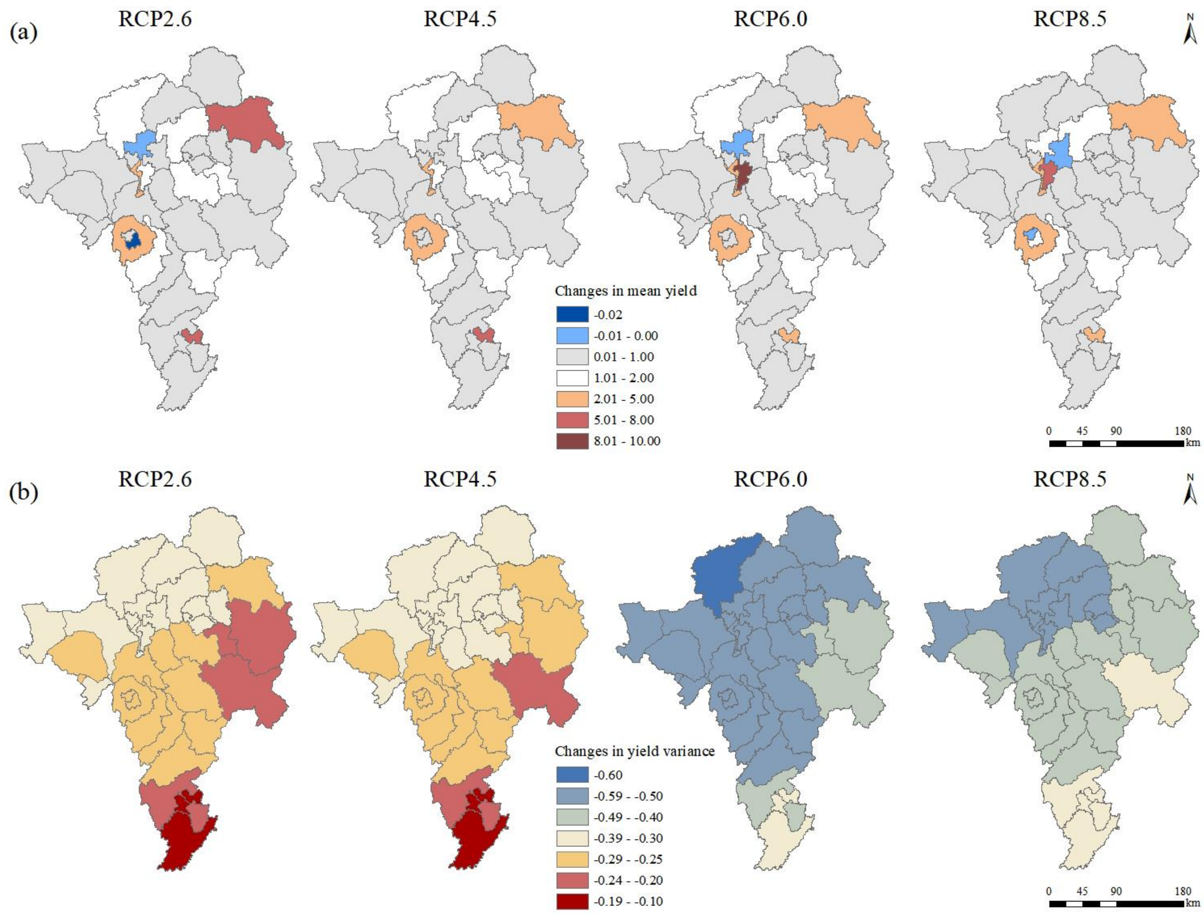

Figure 8. Rate of changes in means (a) and variances (b) of the per unit maize yield during the periods of 2011-2030 and 2031-2050.

4.3 Changes in total maize yield

The total maize yield will significantly increase from 2011 to 2050, with a growth rate of 78.71% (RCP2.6), 79.40% (RCP4.5), 79.01% (RCP6.0) and 78.63% (RCP8.5). In the first two decades, the total yield under RCP2.6, RCP4.5, RCP6.0, and RCP8.5 moderately increase by 38.61%, 35.61%, 30.03% and 18.28%, then exhibit sharp promotion to 124.92%, 149.01%, 148.19% and 161.00% in the latter twenty years. The total maize yields under four RCP scenarios will remarkably differ. Specifically, RCP 2.6 has the maximum total yield of 24.02 megatons in 2030, but it will rank third in 2050. RCP4.5 ranks second in 2030 with 23.50

megatons of maize yield, while it will reach the highest value of 58.52 megatons in 2050. Notably, the total maize yield under RCP 8.5 will remain the minimum in 2030 and 2050 (**Table 3**).

Table 3

Total maize yields in 2030 and 2050 under four RCP scenarios

Scenarios	2030(megatons)	change rate 2011-2030	2050(megatons)	change rate 2030-2050
RCP2.6	24.02	38.61%	54.03	124.92%
RCP4.5	23.50	35.61%	58.52	149.01%
RCP6.0	22.54	30.03%	55.93	148.19%
RCP8.5	20.50	18.28%	53.50	161.00%

Changes in total maize yields will be simultaneously influenced by the per-unit yield and the planting area. In urban areas, e.g., Changchun, Jilin, and Chaoyang, Nanguan and Erdao District of Liaoyuan only have low total yields of maize even if the per-unit yield is at the middle or upper level. In contrast, some counties, such as Nong'an and Gongzhuling, with low per-unit yields will feature higher maize production due to their larger maize planting areas (**Figure 9**). From 2030 to 2050, 67% of counties will experience a decline in cultivated land **(Figure A5)**, but the total maize yields of these counties will increase due to the promotion of per hectare maize yield. Furthermore, climate change will alter the orders of some counties with large planting areas of maize in terms of total yields, e.g., Liuhe, Lishu, Fengman, Dongliao, and Dongfeng County. Under PCR2.6, a slowdown of growth rate in maize yield per hectare in these counties leads to the decline of the total yield ranking. Conversely, RCP8.5 will ensure that most counties have a high total production ranking due to its relatively high growth rate of per-unit yield.

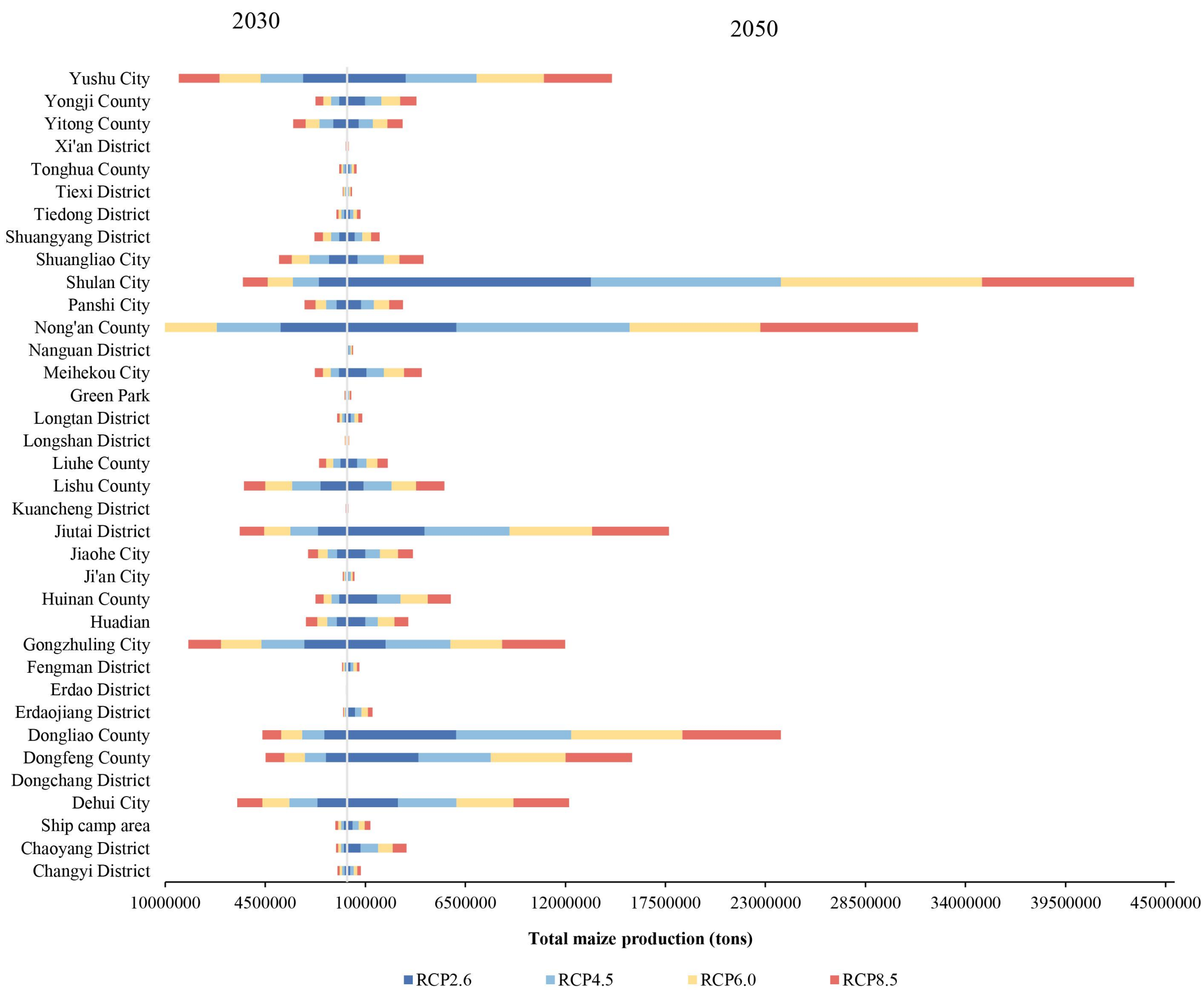

Figure 9. Total maize production at the county level under four scenarios.

5 Discussion

5.1 Comprehensive impact on maize yield

Unlike the previous study, our framework examines the synergistic effects of climate change and land use change on the yield of rain-fed maize in a phaeozem region of Jilin Province. The results show that there appears to be a clear contrast in total yield, potential increment, and spatial pattern between different scenarios, and balanced development is more conducive to maintaining a steady increase in total maize production. For example, Potential maize yield per hectare will significantly increase under the four climate change scenarios from 2011 to 2050, ranked as: RCP2.6> RCP4.5> RCP6.0> RCP8.5. However, RCP2.6 and RCP6.0 will have differences in the maize yield among counties, while RCP4.5 will exhibit a balanced regional pattern of maize production (**Figure 8a**). The total maize yield in 2050 will peak under the RCP4.5 scenario, suggesting the combined effect of temperature, precipitation, and technological progress on maize growth is the best. This scenario's moderate carbon emissions and population and economic growth will help coordinate the conflicts between farmland protection and vegetation conservation and increase overall maize production simultaneously (Hou and Li, 2021; Zhang and Qi, 2010). Notably, an increase in per hectare yield could mitigate the impact of farmland loss on maize yields. The total yield of RCP2.6, RCP4.5, RCP6.0, and RCP8.5 will reach 54.03, 58.52, 55.93, and 53.50 megatons by 124.92%, 149.01%, 148.19% and 161.00% from 2030 to 2050. Although a large amount of cultivated land will be occupied by forest and grassland, the total maize yield under all scenarios still increased exponentially.

The variance of temperature and precipitation during the growing season will affect yield variance (Urban et al., 2012). With the increase in precipitation variance, the variance of maize yields during the period of 2031-3050 will get higher than that in 2011-2030. Under the threat of maize yield reduction caused by variable or extreme climates (Feng et al., 2021; Malik et al., 2021), how to formulate adaptation and mitigation strategies will be a challenging long-term issue for land managers (Iglesias and Garrote, 2015; Zobeidi et al., 2021).

5.2 Policy implications

Our study suggested several implications for agricultural land use and maize production. We can solve many uncertain problems in agricultural production by considering the present and predicted near future land-use, economic and climate scenarios. For example, agricultural technology development can balance land use change, climate change and maize production due to its positive impact on per unit yield (Rojas-Downing et al., 2017). Previous studies suggested that diversification of maize varieties can improve maize resistance to external disturbances caused by extreme weather events and human activities (Altieri and Nicholls, 2017). Maize breeding and biotechnology also have the enormous biological potential to increase grain yield (Foulkes et al., 2011). Researchers have proven that organic matter enhances underground biodiversity, thereby creating suitable conditions for plant roots (Diaz-Zorita et al., 1999; Morugan-Coronado et al., 2022). And proper agricultural management, such as organic agriculture, residue management and crop rotation, can also improve soil quality(Morugan-Coronado et al., 2022).Moreover, regular training and technical guidance for farmers can improve their risk awareness and ability to deal with the risk (Olesen et al., 2011). We suggest that the investment in maize variety and planting technology development should be encouraged to promote the per unit yield of maize. Indeed, accurate prediction of climate change and rational planning of planting scale and planting pattern can advance the reasonability of agricultural management strategies.

5.3 Advantages and limitations

By combining the FLUS and the statistical yield model, this research framework can better describe the joint impact of climate change and land use change on maize yield. Meanwhile, the framework is flexible and can be used as a general decision-making tool for land planning and maize management in different situations. This study documented that climate change will positively impact maize yields in the study area, which is consistent with other simulation studies (Liang et al., 2019; Pu et al., 2020; Zhang et al., 2017a). Since the study area locates in the cold temperate zone, global warming could reduce cold damage and extend the growing season, which will benefit maize yields (Zongruing et al., 2007). From an optimistic point of view, we expect further improvement in planting efficiency (maize yield) as agricultural technology advances and planting management improves in the future. Moreover, the effect of human irrigation on maize growth has been excluded by selecting the study area in a rain-fed region.

This work still has several limitations. First, uncertainty in future climate change will impact the simulation accuracy. The climate conditions shown by different general circulation models (GCMs) in the same region may be quite different (Liu et al., 2013a; Tatsumi et al., 2011). The BCC_CSM1.1 m model was selected for this study to better eliminate the possible errors in the prediction results. Although the BCC has been applied to a number of studies on grain production in northeast China (Pu et al., 2020; Xie et al., 2020), there is still room for improvement. Second, existing studies have shown that incorporating remote sensing into statistical models can improve forecasting accuracy, especially for large-scale regions (Laudien et al., 2020).

6 Conclusion

This study proposes an integrated framework for maize yield prediction by combining the SD and the FLUS model with the statistical model. Future maize yield change can be simulated under the four RCP scenarios. The proposed framework is flexible and suitable for applications in any other regional studies. The simulations help provide scientific guidance for the decision-making of agricultural management.

We conclude that an increase in per-unit yield in the study area will mitigate the negative impact of farmland loss on the total maize yield. Although cultivated land is likely to decrease from 2030 to 2050, the total maize yields under RCP2.6, 4.5, 6.0, and 8.5 will still increase by 124.92%, 149.01%, 148.19% and 161.00%. Under the four RCPs, disparities in total maize yields will differ across the region, especially under RCP2.6. In comparison, RCP 4.5 features more balanced and stable, which will be conducive to ensuring maize yields and benefitting regional sustainable development in the future.

Facing the threat of variable or extreme climates and the further widened yield gap between different counties, we need to implement the differentiated policies of agricultural production and farmland protection, including strengthening cultivated land protection and crop management in low-yield areas, as well as adoption of adaptation and mitigation measures.

Declaration of Competing Interest

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

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Estimation of maize yield incorporating the synergistic effect of climatic and land use change: A case study of Jilin, China

Xinyuan Wen[1], Dianfeng Liu[1,2*], Mingli Qiu[1], Yinjie Wang[1] and Jiqiang Niu[3]

1 School of Resources and Environmental Sciences, Wuhan University,430079, Wuhan, China.

2 Key Laboratory of Digital Cartography and Land Information Application Engineering, Ministry of Natural Resources, 430079, Wuhan, China.

3Key Laboratory for Synergistic Prevention of Water and Soil Environmental Pollution, Xinyang Normal University, Xinyang, China.

*Corresponding author: Dianfeng Liu (liudianfeng@whu.edu.cn)

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Text A1.

The improvement in agricultural mechanization ($machine$, $machine^2$) and county-fixed effects ($county$) explain 40.3% of the county-level yield variance, which reflects the mean and the rapid improvement pace of crop have presented uneven spatial distribution since 2000. T, P, and their square terms explain 3.3% of the county-level production variance. Sunshine hours (SH) has an insignificant coefficient of determination, and is excluded in the final model (**Equation A1**). **Table A1** shows the model coefficient and significance test.

$$log\,(yeild) = 0.000128 * machine^2 - 0.0055 * machine + 1.598 * T - 0.043 * T^2 + 0.006394 * P - 0.0000262 * P^2 - 6.234 \quad \text{(A1)}$$

Considering the error value, the model can be written as:

$$log\left(y_{county,year}\right) = log\left(\hat{y}_{county,year}\right) + log\left(\epsilon_{county,year}\right) \quad \text{(A2)}$$

The hat symbol (^) indicates the estimated value of yield production. Assume that the error is independent of the estimated value $\log(\epsilon)$. All terms in the above equation are logarithmic. We first take the exponents on both sides of **(Equation A2)** to calculate the yield per hectare.

$$y = e^{log\,(\hat{y})} e^{log\,(\epsilon)} \quad \text{(A3)}$$

It is crucial to consider the yield error when comparing the yield variance between 2011-2030 and 2031-2050. We can calculate the variance of the final production, substituting the variance values of the residuals at all levels (Attached **Table A2**):

$$Var(y) = (E[\log(\hat{y})])^2 \times Var(\log(\epsilon)) + (E[\log(\epsilon)])^2 \times Var(\log(\hat{y})) + Var(\log(\hat{y})) \times Var(\log(\epsilon)) \quad \text{(A4)}$$

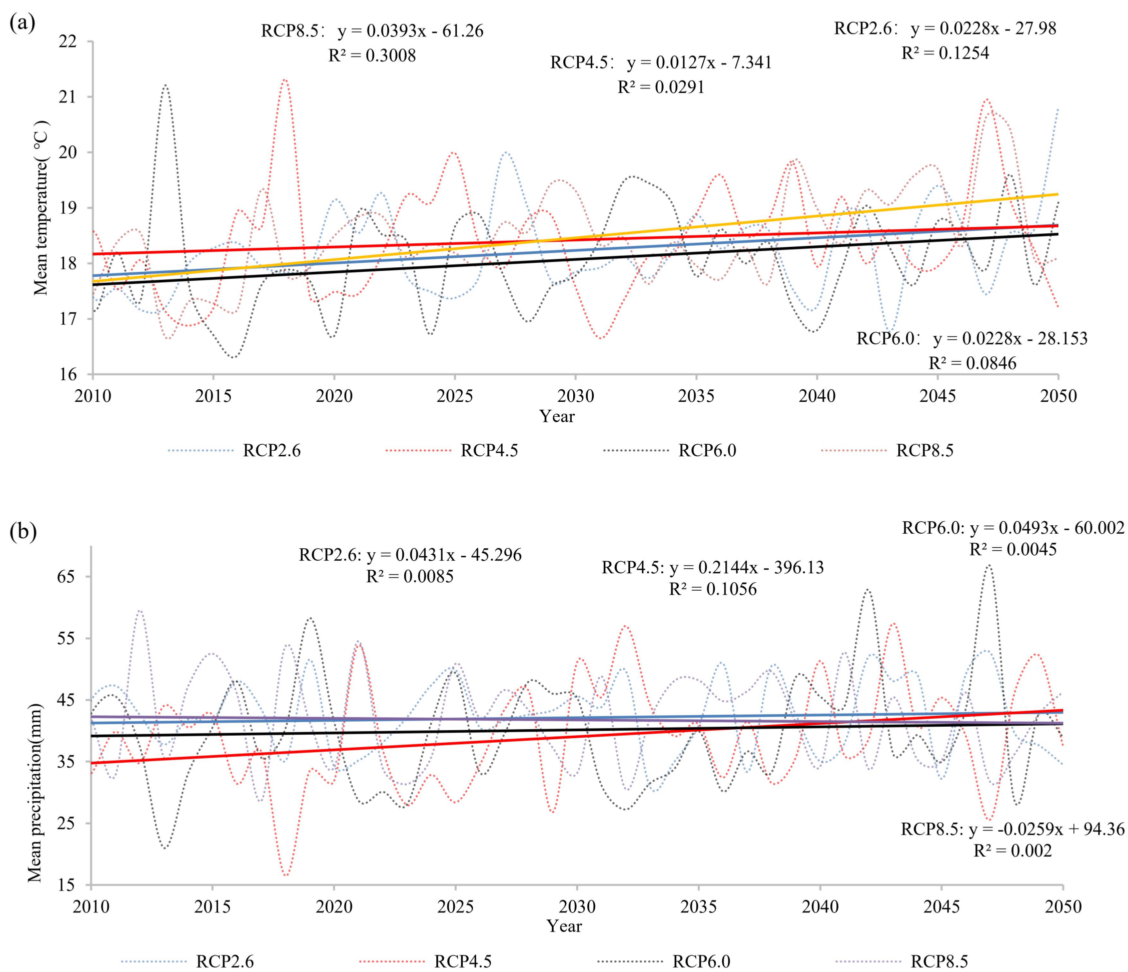

Figure A1. (a)Average temperature in the study area from May to September under RCPs; (b) Average precipitation in the study area from May to September under RCPs.

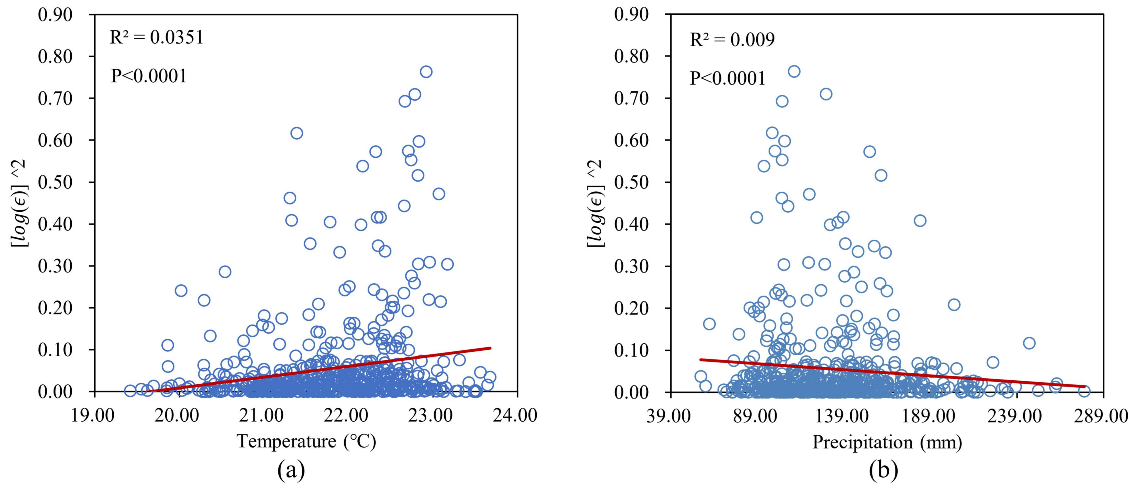

Figure A2. Least-squares regression diagram of the square of the production residuals and the average T and P during the training period.

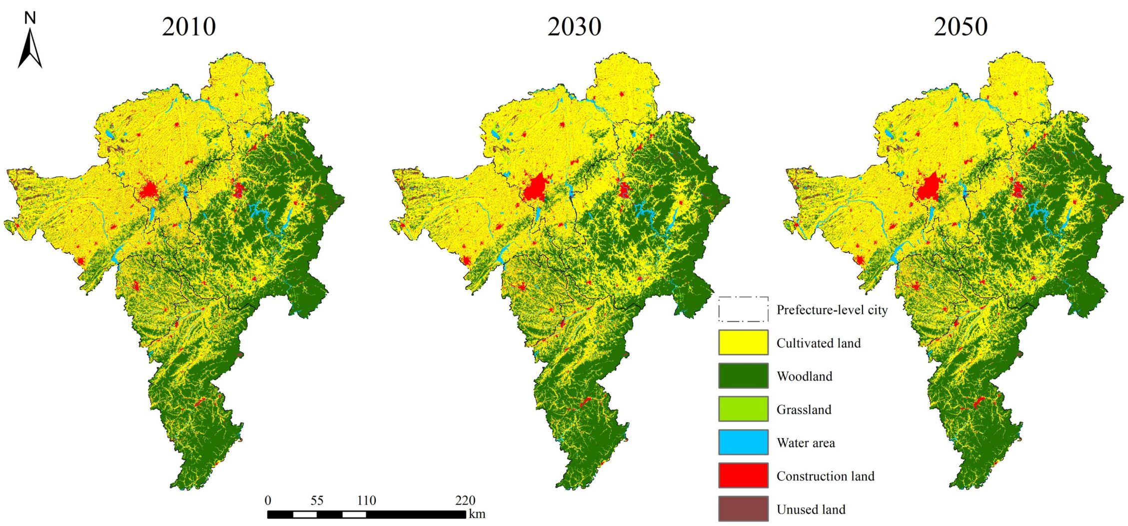

Figure A3. Land use maps in 2010, 2030 and 2050.

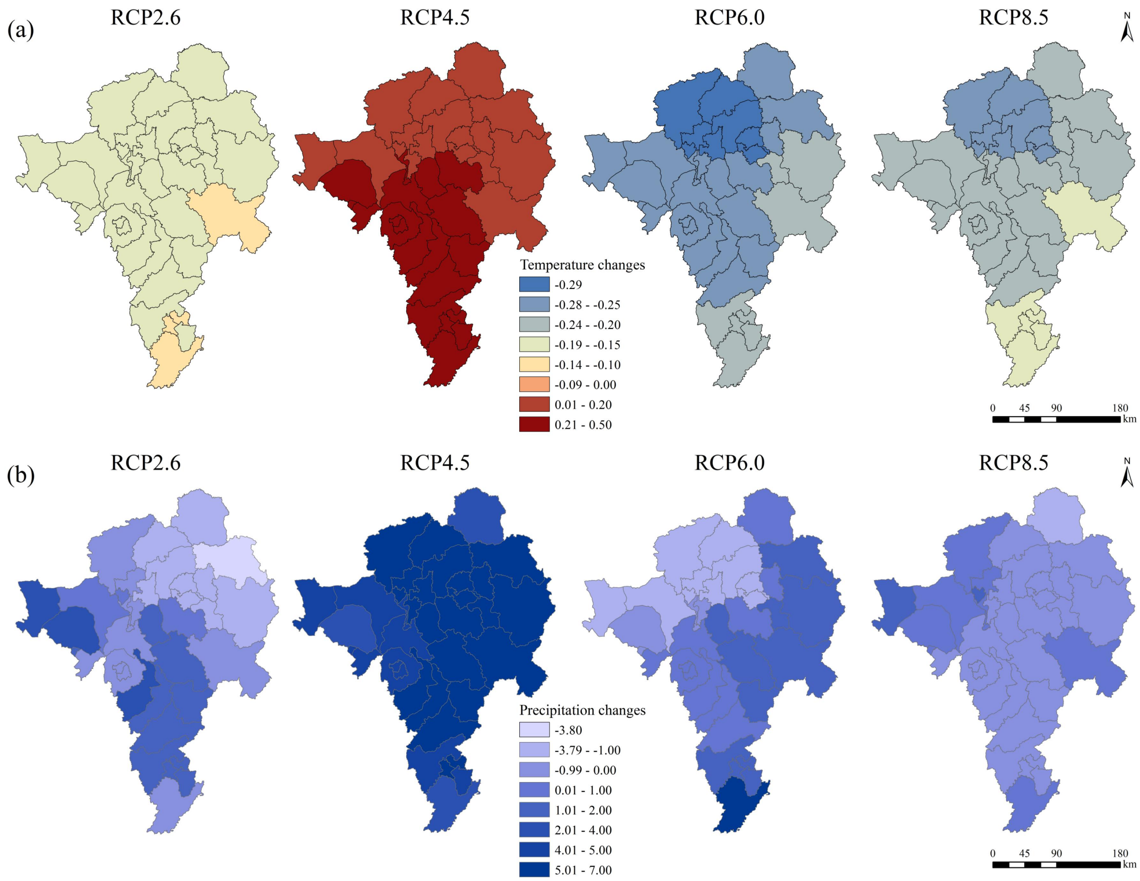

Figure A4. (a) Temperature variation by county from 2011-2030 to 2031-2050; (b) Precipitation varies by county from 2011-2030 to 2031-2050.

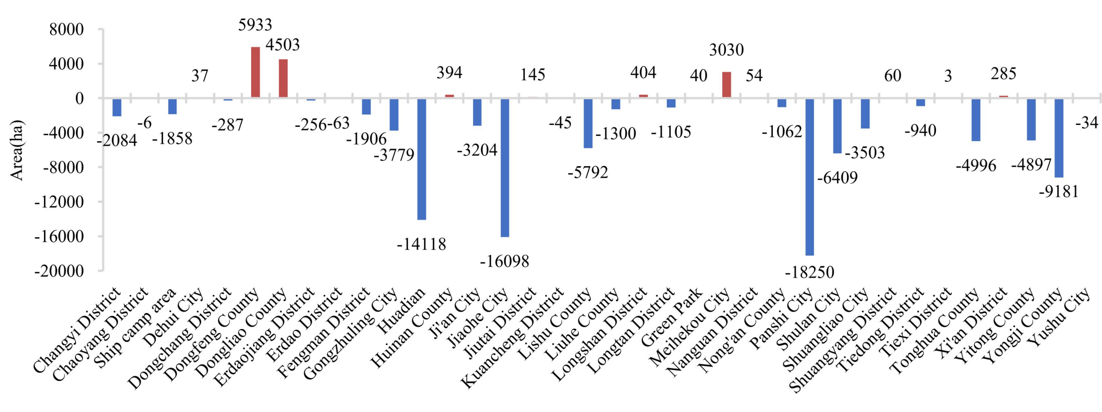

Figure A5. Changes in cultivated land areas at county level from 2030 to 2050.

Table A1

Regression coefficients.

Model	Unstandardized coefficient		t	Sig.
	B	Standard error		
(constant)	-6.226	7.759	-0.802	0.423
T	1.598	0.788	2.029	0.043
T^2	-0.043	0.020	-2.163	0.031
P	0.006	0.003	2.254	0.025
P^2	-2.622E-05	0.000	-2.146	0.032
$machine$	-0.006	0.001	-4.633	0.000
$machine^2$	1.284E-04	0.000	3.153	0.002
SH	2.750E-04	8.02 E-04	0.342	0.732
Area=Dongfeng County	0.243	0.104	2.329	0.020
Area=Dongchang District	0.265	0.135	1.971	0.049
Area=Dongliao County	0.251	0.105	2.392	0.017
Area = Fengman District	0.095	0.115	0.821	0.412
Area=Jiutai City	0.035	0.104	0.342	0.733
Area = Erdao District	-0.409	0.102	-4.025	0.000
Area = Erdaojiang District	0.148	0.134	1.105	0.269
Area=Yitong County	0.267	0.102	2.623	0.009
Area=Gongzhuling City	0.652	0.105	6.212	0.000
Area=Nong'an County	0.431	0.105	4.085	0.000
Area = Nanguan District	-0.019	0.109	-0.173	0.863
Area=Shuangyang District	0.316	0.108	2.920	0.004
Area = Kuancheng District	-0.400	0.102	-3.920	0.000
Area=Dehui City	0.298	0.106	2.813	0.005
Area=Changyi District	0.092	0.103	0.888	0.375
Area=Chaoyang District	-0.106	0.113	-0.942	0.346
Area = Liuhe County	0.255	0.112	2.263	0.024
Area = Huadian City	-0.020	0.121	-0.167	0.867
Area=Meihekou City	0.087	0.104	0.834	0.405
Area = Lishu County	0.724	0.105	6.916	0.000
Area = Elm City	0.313	0.104	3.019	0.003
Area=Yongji County	0.028	0.103	0.268	0.788
Area=Panshi City	0.106	0.103	1.024	0.306
Area = Green Park	0.055	0.119	0.461	0.645

Area = Shulan City	0.200	0.111	1.810	0.071
Area = Ship Camp Area	0.063	0.105	0.599	0.549
Area = Jiaohe City	0.102	0.116	0.877	0.381
Area = Xi'an District	-0.042	0.103	-0.412	0.680
Area=Huinan County	0.351	0.112	3.130	0.002
Area=Tonghua County	-0.051	0.110	-0.460	0.646
Area=Tiedong District	0.236	0.107	2.200	0.028
Area = Tiexi District	0.449	0.185	2.427	0.016
Area = Ji'an City	-0.098	0.109	-0.894	0.372
Area = Longshan District	-0.055	0.102	-0.538	0.591
Area=Longtan District	0.091	0.105	0.868	0.386

Note: B and Beta are regression coefficients; Sig. is the P-value, which represents the significance in the hypothesis test.

Table A2

Variance of county residual error.

region	$Var(\log(\epsilon))$	region	$Var(\log(\epsilon))$
Changyi District	0.025572075	Liuhe County	0.044541441
Chaoyang District	0.195618882	Yongsan District	0.088251022
Ship Camp Area	0.014275893	Longtan District	0.019158748
Dehui	0.033632781	Green Park	0.249584034
Dongchang District	0.014318566	Meihekou	0.009294256
Dongfeng County	0.026302486	Nanguan District	0.14462959
Dongliao County	0.049171297	Nong'an County	0.011689685
Erdaojiang District	0.031237137	rock city	0.01400162
Erdao District	0.431996676	Shulan	0.01074008
plump area	0.048536536	Shuangliao	0.038542727
Gongzhuling	0.010237088	Shuangyang District	0.072074432
Huadian	0.026221195	Tiedong District	0.039590128
Huinan County	0.070030835	Tiexi District	0.079287917
Ji'an	0.023745877	Tonghua County	0.011766734
Jiaohe	0.046481507	Xi'an District	0.344605244
Jiutai District	0.0508169	Yitong County	0.071153589
Kuancheng District	0.28749462	Yongji County	0.043845527
Lishu County	0.030609236	Elm City	0.012829379