IMPACT OF CLIMATE AND AGRICULTURAL MACHINERY ON CORN YIELD: AN IN-DEPTH ANALYSIS

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(Received 19th Apr 2024; accepted 2nd Sep 2024)

Abstract. In global agriculture, the challenges facing agricultural production are escalating, especially in the current international situation, which underscores the urgency of addressing food production issues. This study aims to investigate various factors influencing the food production process and yield fluctuations, crucial for developing efficient agricultural planting strategies and adjusting related policies. It combines natural science and social economics perspectives, taking maize production in Qiqihar City, Heilongjiang Province as the research object. Using data from 1995 to 2020, it examines the comprehensive effects of natural climate and agricultural mechanization development level (AMDL) on maize production and constructs an AMDL evaluation system. To predict future agricultural development more accurately, this paper proposes the climate economic prediction model(C-D-AS), incorporating a multi-variable system. To ensure research accuracy and reliability, the TensorFlow 2.4.0 framework was used for multiple linear regression based on the gradient descent method, and prediction results were compared and analyzed. The results indicate that the variation in the effects of climate and AMDL on crop yield is as high as 62.1%, and the correlation between predicted results and real data is 95.3%. This study not only provides robust theoretical support for local agricultural production but also offers the government and farmers a new understanding of the vulnerability and adaptability of the agricultural system, with far-reaching implications for sustainable agricultural development.
Keywords: *maize yield, multivariate analysis, sensitivity analysis, adaptability strategies, sustainable agriculture*

Introduction

In modern agriculture, agricultural practitioners necessitate real-time, precise, and exhaustive comprehension of the farmland ecosystem and crop growth conditions. As such, they must analyze, synthesize, and formulate decisions founded on agricultural information data. Such approach is essential for ensuring consistent advancements in grain production and fostering sustainable development in agriculture (Yue et al., 2020). The technologies of agricultural information perception, parsing, prediction, and processing are significant factors in modern agricultural production. The emergence of a

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2206_53615381

new round of technological revolution and industrial transformation has fostered a large number of strategic emerging industries, including machine learning, deep learning and other high-techs, which have been gradually applied in various areas of agricultural production (Huang et al., 2023). The profound amalgamation of agriculture and technology has delivered robust information support for agricultural production processes, substantially advancing the progression of modern agriculture.

In recent years, as an emerging domain, intelligent agriculture has facilitated farmers in optimizing cultivation techniques and agricultural yields by incorporating innovative technologies such as agricultural big data (Luo et al., 2021), the Internet of Things, satellites, drones, and others (Bernardi et al., 2018). Governments, agricultural scientists, and farmers from various countries have been engaged in collaborative efforts to enhance crop yields and address challenges related to food supply and food security. However, the efficacy of such initiatives has not yielded substantial improvements thus far. When examining the factors influencing crop yields, both domestic and international experts and scholars have predominantly focused on investigating the factors that impact corn production and its production potential. Such research tended to focus on the climatic aspect, falling within the domain of single-factor analysis. Several scholars have also investigated the spatial distribution of climate productivity over time and space, conducted correlation analysis of meteorological factors that affect climate productivity, and identified significant spatial differences (Li et al., 2018; Wei, 2021). Despite such endeavors, this research was primarily confined to investigating spatial dimensions. In terms of research on agricultural mechanization, there has also been a tendency to improve agricultural production efficiency and resource utilization efficiency, in order to break the constraints of capital and technology on agricultural operators (Weber et al., 2022), improve scientific and accuracy decision-making by producers, reduce agricultural production risks, and focus on the technological development of hardware infrastructure. At present, there is a scarcity of research on the combined impact of natural climate change and AMDL factors on crop yields. Thus, further research is imperative to delve deeper into this topic and broaden its scope. The influence of climate factors on crop yields is evident. Climate variations can result in alterations in precipitation patterns, temperature levels, and light availability, consequently influencing crop growth and development (Zhang et al., 2021). It is imperative for farmers to develop more effective strategies for coping with the increasingly frequent extreme weather events attributable to climate change (Nyasulu et al., 2022). At the same time, mechanization is a significant technological mean in agricultural production, which has a considerable impact on corn yields (Isaak et al., 2020). The development of agricultural mechanization (AM) renders planting, fertilization, irrigation, harvesting and other agricultural activities more efficient and accurate, reducing labor needs and improving production efficiency. The introduction of novel production technologies into agricultural regions aims to augment corn production and, from a technical standpoint, enhance the quality of corn (Askerov, 2021). Deepening the research and understanding natural climate and AMDL on crop yields can facilitate better understanding of the vulnerability and adaptability of agricultural systems. This knowledge can also aid in better understanding and predicting the functioning of agricultural systems (Liu and Li, 2023).

In the present study, natural climate factors were first selected to analyze the climate mutation effect. Secondly, indicators of AMDL were quantified and a development level evaluation model was designed. A corn production potential prediction model with dual factors was then comprehensively designed. Subsequently, the practicality of the method was verified based on data, thereby providing scientific evidence for agricultural production and formulating corresponding technical and management strategies for increasing crop yields and adapting to climate change, in response to challenges such as climate change and food security.

To gain a comprehensive and reliable analysis of the impact of climate and AM levels on corn production, it is imperative to take into account various models while considering a wide array of factors encompassing natural science and socio-economic aspects. By deeply understanding the advantages and limitations of these different models, a more comprehensive understanding of this complex relationship can be achieved. In view of this, mathematical and economic thinking were combined in the present study. Further, the Cobb-Douglas production function was adopted as the theoretical basis, as well as the gradient descent method. Ultimately, the research culminated in the development of a C-D-AS economic-climate model for corn yield, integrating various influencing factors identified during the study. The model considers the analysis of climate change effects on corn yield, as well as comprehensive consideration of the impact of various uncertainties such as AM on corn production. The present research holds greater practical significance, and the availability of data aligns well with the research scope, rendering it a more feasible and scientifically grounded endeavor.

Material and Methods

Study area and data collection

The study focused on maize production in Qiqihar City, Heilongjiang Province, China. Data were collected from 1995 to 2020, encompassing various aspects such as climate conditions, agricultural mechanization development level (AMDL), and maize yield. Data sources included local agricultural bureaus, meteorological stations, and statistical yearbooks.

Variables and indicators

Climate variables considered included temperature, precipitation, sunshine hours, and humidity. AMDL was assessed based on mechanization equipment usage, technological advancements, and government policies related to agricultural mechanization. Maize yield was the primary dependent variable, representing the output of maize production.

Evaluation system for AMDL

An evaluation system for AMDL was constructed using a combination of quantitative and qualitative indicators. Quantitative indicators included the number of agricultural machines, mechanization rates, and investment in agricultural technology. Qualitative indicators encompassed policy support, farmer awareness, and technological adoption rates.

Model construction

The C-D-AS climate economic prediction model was developed to analyze the combined effects of climate and AMDL on maize production. The model integrated multiple variables and employed a system dynamics approach to simulate and predict agricultural development trends.

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Data analysis and prediction

TensorFlow 2.4.0 framework was utilized for data analysis. Multiple linear regression based on the gradient descent method was conducted to identify the relationships between climate, AMDL, and maize yield. Prediction results were generated using the C-D-AS model and compared with actual data to assess model accuracy.

Validation and reliability

Model validation was performed through cross-validation techniques to ensure the robustness of the predictions. Correlation analysis was conducted to assess the strength of the relationship between predicted results and real data. Sensitivity analysis was performed to identify the key factors influencing maize yield.

Performance analysis of research methods for agricultural impact factors

Existing research on the factors influencing corn production is progressively advancing, becoming increasingly comprehensive and grounded in scientific methodology. Many studies have investigated the impact of different factors on corn growth potential and yield from perspectives such as crop type itself, natural factors, and mechanicalization level.

Natural science perspective

Using historical data, statistical methods were applied to model the impact of climate factors on corn production (Chen et al., 2013; Xu et al., 2021). Input data on corn growth, weather, soil, and management conditions, regional climate models were used to directly simulate the impact of climate change on corn production (Mistry and Bora, 2019; Li et al., 2020; Zhang et al., 2021).

Professor David B. Lobell is a distinguished American scholar in the field of agriculture and food security, who has made significant contributions to the field. He has conducted multiple investigations into the impact of climate change on crop production (Lobell and Asseng, 2017; Tebaldi and Lobell, 2018; Lobell et al., 2019; Benami et al., 2021), including artificial climate or field control experiments, using crop models to simulate and observe research, and observing statistical methods. Through his time series research, he has consistently relied on data and repeatedly showcased how distinct regions respond to varying climates. This underscores the significance of utilizing historical data in research endeavors. Shi et al. (2013) Used historical data on corn production and weather to calibrate a relatively simple regression equation statistical model, which has been extensively adopted in their research. However, there has been a scarcity of research in which previous statistical models used to determine the contribution of climate on corn production were systematically reviewed.

Social economic perspective research

Many scholars have analyzed the changes in corn production within the framework of modern agricultural practices, emphasizing the role of AM in this context, with a specific focus on crop-related aspects. Numerous scholars have also explored such changes from different perspectives. Calvin and Fisher-Vanden (2017) designed an experiment to compare and measure the significance of interaction effects through the use of methods such as a process-based crop model, a statistical crop model, and an integrated evaluation

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model. In the study, the impact of different modeling methods on United States (excluding California) corn production was analyzed. Roberts et al. (2017) used a simple process-based crop model, a simple statistical model, and a combination of the two models to predict actual corn yields with a representative sample of farmers in the US Corn Belt region.

Following the calibration of the statistical model, the process model (SSM) exhibited a slightly superior prediction accuracy compared to the statistical model alone. However, the combination model significantly outperformed both individual models in terms of predictive performance. The statistical model and the combined model revealed more adverse effects linked to extreme high temperatures, whereas the SSM did not account for this factor. This highlights the importance of incorporating multi-factor combinations when investigating factors influencing corn production. Chandio et al. (2020) used the Generalized Method of Moments (GMM) model to analyze data spanning from 1980 to 2018 in Sichuan Province, China. Findings were made that from an economic perspective, there was a positive link between fertilizer use and crop yield, and corn production significantly increased through mechanization, demonstrating that the development level of AM had a positive contribution to corn yield. Using weather data as input, Kolberg et al. (2019) Simulated springtime machinability, availability, aging costs and mechanization management in central Norway by means of machinability models and mechanization models. The results revealed that following the same pattern, there were only small changes in profitability and mechanized management across different regions. To evaluate long-term effects, Zhang et al. (2022) used fully modified ordinary least squares (FMOLS) and dynamic ordinary least squares. The results demonstrated that agricultural machinery had a significant contribution to corn yield and there was a bidirectional causal relationship. Aziz and Chowdhury (2022) conducted research on the agricultural impact of mechanization in Bangladesh, focusing on the degree of mechanization. The study highlighted the importance of enhancing mechanization demand, ensuring a stable supply of mechanization, reinforcing institutions essential for mechanization development, and prioritizing improvements in AM for small-scale farmers. This highlights the critical role of studying the level of AM in fostering agricultural development.

Most existing studies have been based on a single perspective. In the present study, two perspectives were combined to explore their main factors. The main climate factors extracted from the natural perspective were analyzed. Meanwhile, the impact factors of AMDL from the perspective of social economy were assessed, so as to analyze the impact path of agricultural mechanization. The utilization of the C-D production function in conjunction with regression models aligns more closely with the research scope and offers a comprehensive, specific, feasible, and scientifically rigorous approach to analysis.

Model design of the impact of climate and agricultural mechanization development level on corn production potentiality

The impact of climate and AMDL on crop production potentiality is an extremely complex systematic problem, which is influenced by numerous interacting factors. As such, to establish an accurate model, factors such as climate, agricultural machinery power, crop type, agricultural management measures, and farmer benefits need to be taken into account, as well as constant validation and adjustment of the model to improve its reliability and applicability. The overall research route of this paper is shown in *Fig. 1*.

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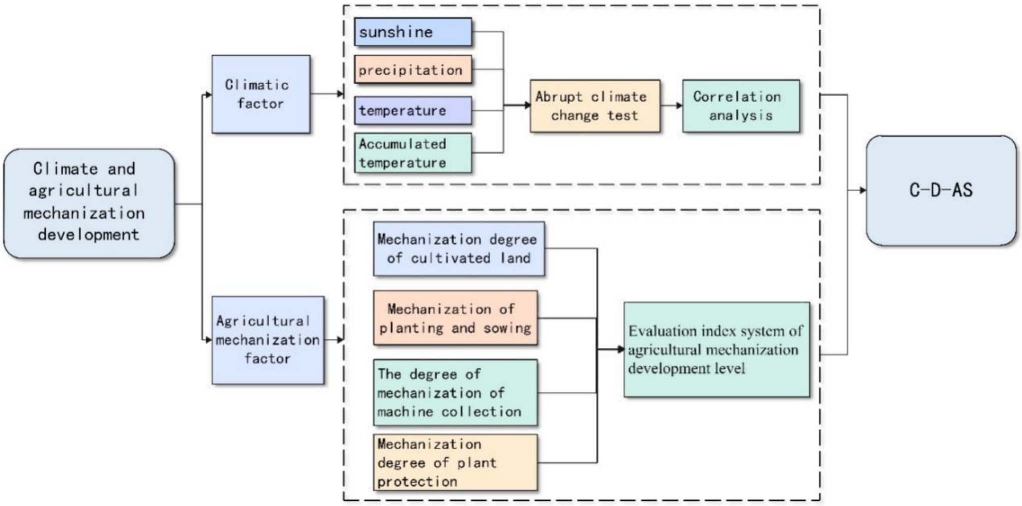

Figure 1. *Technology roadmap*

Based on the impact of climate factors on maize production potentiality model design

Qiqihar City is located in the Songnen Plain in Northeast China, with a longitude ranging from 122°24′ to 126°41′ and a latitude ranging from 46°13′ to 48°56′. It is located in the first accumulation zone. The city has distinct geographical and climate characteristics and belongs to the temperate continental monsoon climate, with the growing season mainly from May to September. In the present study, when analyzing the comprehensive factors that affect maize growth potential, three perspectives were selected: climate factors in the growing season in northern China, indicators of agricultural mechanization, and the development level of climate and AM in the growing season. As an area with a high degree of mechanization, there are a variety of farm sizes, ranging from vast farms of large reclamation enterprises to medium-sized cooperatives and family farms, as well as small farms and family contracted land. The main varieties of corn planted in Qiqihar include Fuer116, Fuxing 188, Jinnuo 195, etc. They are all hybrid varieties of corn, and as high-quality and efficient varieties of corn, they have been planted in a large area, and have performed well in yield, stress resistance, adaptability and other aspects. And these three varieties in the local corn planting area occupies the majority proportion. Therefore, this paper will focus on the analysis of the yield and planting area of these three varieties, and discuss their important contribution to the total production, data from the statistical yearbook. At the same time, macro time series panel data and micro-maize yield were used to analyze the model. The present study operated under the assumption that agricultural producers are market-rational individuals primarily driven by the pursuit of agricultural production profits. In this context, such assumption was employed to design a regression analysis model utilizing time series data. The function of the model is shown in *Eq.(1)*:

$$CY_{S,P,T,ACT} = \beta0 + \beta1^{*} S + \beta2^{*} P + \beta3^{*}T + \beta4^{*} ACT \ \ldots + \beta n^{*}xn + \varepsilon \qquad \text{(Eq.1)}$$

In *Formula (1)*,where CY, S, P, T, and ACT represent maize yield, sunshine hours, precipitation, temperature, and accumulated temperature, respectively. ε represents the disturbance term. The choice of accumulated temperature as an indicator of climate factors is motivated by the study area's northern location, characterized by relatively cold

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN1785 0037 (Online)
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climate conditions. This decision was made because monitoring changes in accumulated temperature throughout the growing season provides a more accurate representation of the influence of climate factors on crop growth.

Drawing upon the theory of natural climate abrupt changes and conducting a significance level test at the 5% threshold. *Fig. 2* shows the results of climate abrupt change calculated based on Mann-Kendall (M-K) test method. Specifically, subplot (a) illustrates the outcomes of the sunshine duration mutation test, highlighting any abrupt changes or trends in sunshine patterns. Subplot (b) showcases the results of the precipitation mutation test, revealing potential shifts or anomalies in precipitation levels. Subplot (c) depicts the temperature mutation test results, indicating any sudden alterations or deviations in temperature trends. Lastly, subplot (d) exhibits the accumulated temperature mutation test results, shedding light on any abrupt variations or patterns in accumulated temperature over the study period. *Fig. 2* reveals that between 2002 and 2016, the study area consistently exhibited a declining trend in sunshine hours. However, a notable and statistically significant upward trend has been observed since that time. Despite such findings, precipitation exceeded the upper limit zero boundary value in 2018 and had a significant upward trend. The temperature and accumulated temperature showed a slight upward trend with minimal difference. Overall, the indication is that further research based on climate abrupt changes has theoretical basis.

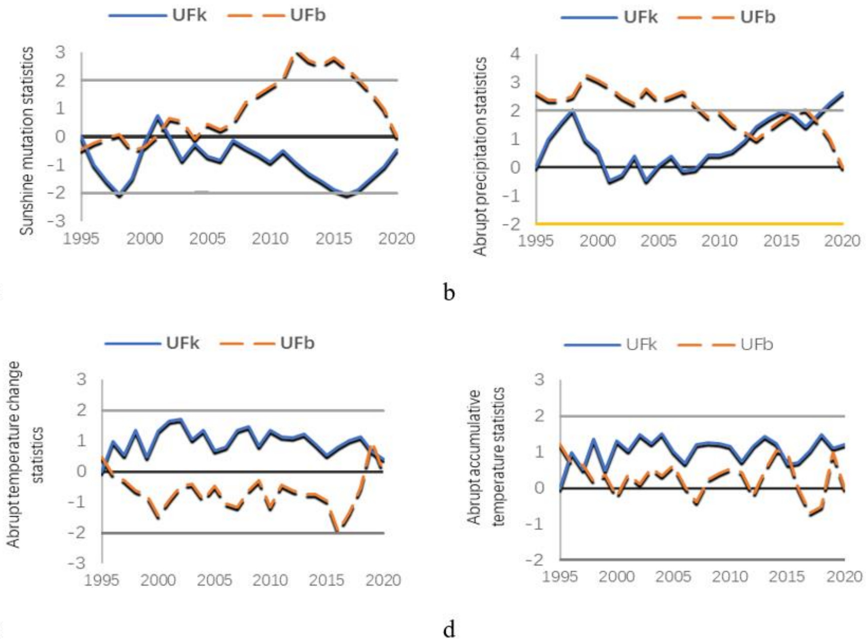

Figure 2. *Results of climate Mutation test in Qiqihar during 1995-2020 (Note: UFk and UFb represent the values in the statistical series calculated in time series order and reverse order respectively in the climate abrupt change test, and they are used together to assess the trend change of the series and to identify abrupt points)*

Figure 3 illustrates the regression relationships between various climatic variables and crop yield. Specifically, subplot (a) presents the regression analysis of sunshine duration and yield, revealing the trend and strength of their association. Subplot (b) showcases the regression relationship between precipitation and yield, highlighting any significant

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correlations or patterns. Subplot (c) depicts the regression analysis of temperature and yield, indicating how temperature variations impact crop production. Lastly, subplot (d) exhibits the regression relationship between accumulated temperature and yield, shedding light on the cumulative effect of temperature on crop yield over the study period. Based on the perspective of maize yield, the regression results in *Fig. 3* between climate and yield indicate that the fluctuation trend of maize yield was positively correlated with the curves of sunshine hours, precipitation, and accumulated temperature. Among them, while the insolation is at the mutation point, the yield fluctuates significantly, indicating that the yield has a relatively captured correlation with the insolation hours., precipitation had a relatively obvious correlation, and with the increase in temperature, the yield also exhibited a more significant upward trend. Such findings indicate that maize yield was closely related to precipitation and that precipitation also exhibited obvious inter-annual variation and seasonal changes that were not captured in the analysis. A further observation can be made that appropriate sunshine hours and increasing temperature can also help to improve maize yield.

Although the D-W test shows weak correlation, VIF < 5 proves the independence of each variable.

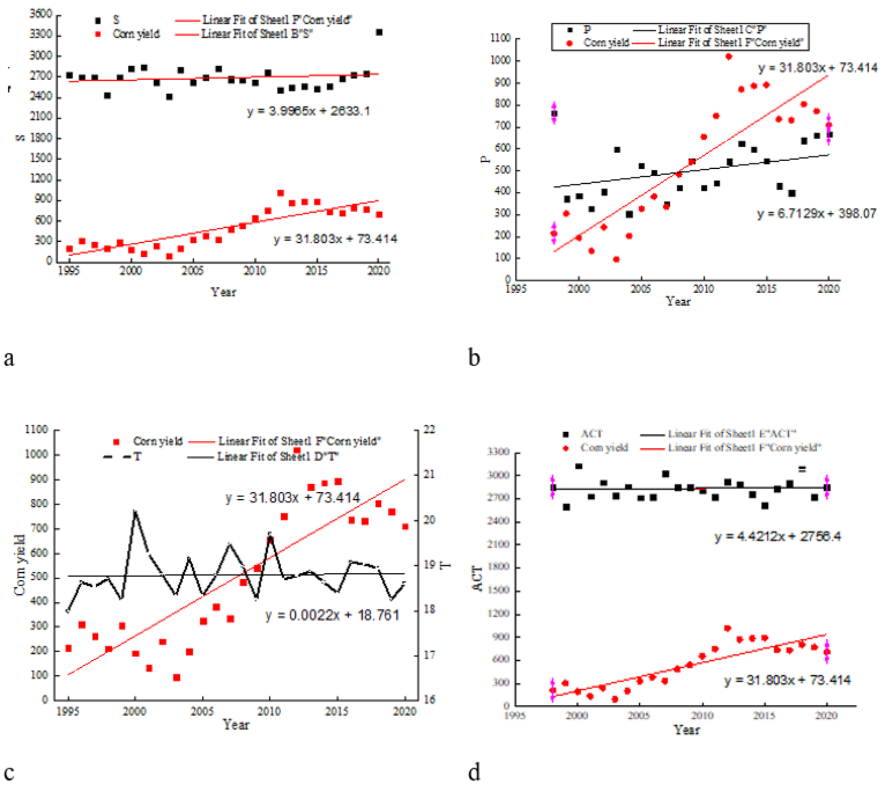

***Figure 3.** Relationship between climate and crop growth potential in Qiqihar during 1995-2020*

Machinery development level evaluation model design

To evaluate the impact of different levels of AM on crop production, the evaluation model of AM was used. The AM evaluation model correlated agricultural machinery indicators with crop growth and yield to determine the extent of the impact of AM on crop production. The study area belongs to an important agricultural region in

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Heilongjiang Province, where the level of AM has been well developed and promoted. Building upon the research conducted by prior scholars and referencing the criteria for selecting agricultural machinery indicators established in relevant studies (Ye et al., 2014; Wang, 2016) and considering the comprehensive progress and practical applications in the region in recent years, adjustments were made to the selection criteria and the number of indicators. This led to the development of a comprehensive assessment criterion system for the level of agricultural mechanization, utilizing the inductive parameter method. The parameter values were normalized using the ratio method, and the standard values of the development level of AM were calculated based on statistical models.

When evaluating the development level of agricultural mechanization, the model was established and evaluated from the perspective of agricultural machinery development level. The model analyzes not only the impact of AM on maize production potential but also the contribution of AMDL comprehensively.

The overall evaluation formula for the development level of machinery is shown in *Eq.(2)* as follows:

$$Y_{A1,\ A2,\ A3,\ A4,\ \varepsilon} = \sum_{i=0}^{n} \boldsymbol{ai} * \boldsymbol{Ai} + \boldsymbol{\varepsilon} \qquad \text{(Eq.2)}$$

In *Formula (2),* where A1 reflects the degree of mechanized farming and sowing in the study area, and four indexes are selected as secondary indexes, and the formula is as follows:

$$A1_{A11,\ A12,\ A13,\ A14,\ \varepsilon} = \sum_{i=0}^{n} \boldsymbol{a1i} * \boldsymbol{A1i} + \boldsymbol{\varepsilon} \qquad \text{(Eq.3)}$$

In *Formula (3),* where A11 represents the degree of mechanization of land cultivation; A12 represents the degree of mechanization of seeding; A13 represents the degree of mechanization of harvesting; and A14 represents the degree of mechanization of plant protection. The weight of each indicator is 50%, 20%, 20%, and 10%, respectively. The specific variables are shown in *Table 1.*

Table 1. *Mechanical tillage and sowing mechanization operation degree index during 1995-2020*

Variable Number	Variable Name	Variable Explanation	Variable Dimension	Maximum Value	Minimum Value	Average Value	Sample Size
A11	Arable land	Mechanization degree of cultivated land	%	99.7	63.97	90.05	26
A12	Planting and sowing	Mechanization of planting and sowing	%	98.46	67.69	88.48	26
A13	receiver	The degree of mechanization of machine collection	%	97.29	87.42	91.81	5
A14	Plant protection	Mechanization degree of plant protection	%	90.5	76.078	81.82	5

Note: Due to data gaps between 1995 and 2015 for A13 and A14, the minimum value in the data series was used to supplement the missing values

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Based on the data in *Table 1* and the graphical data in *Fig. 4 and Fig. 5*, an observation can be made that after experiencing the transition from planned economy to market economy, AM officially entered the initial stage guided by market demand. Mechanical cultivation and seeding experienced a short-term decline due to several factors impacting the mechanized cultivation of land. These factors included challenges in accurately reporting the mechanized farmland area, complexities in obtaining comprehensive farmland area data, and limited adoption of large-scale seeding machinery. After the introduction of the "Two Free, One Subsidy" policy in 2004, which greatly encouraged farmers' enthusiasm for farming, the degree of mechanization showed a generally optimistic and steadily increasing trend. Further, the establishment of management cooperation organizations, the deployment of high-powered agricultural machinery, the dissemination of advanced planting techniques, the development of high-quality farmland, and the enhancement of measures for safeguarding black soil collectively contributed to mechanical cultivation and seeding surpassing the 98% mark in the study area for both 2014 and 2018. These rates significantly exceeded the levels of mechanized operations observed in other regions across China. The overall operation level has shown a downward trend since 2017, primarily due to changes in crop types. In addition, with more rural laborers moving to cities for work and farmers choosing to rent their land through contracting systems, there are difficulties in reducing planting difficulties and maintaining traditional farming methods.

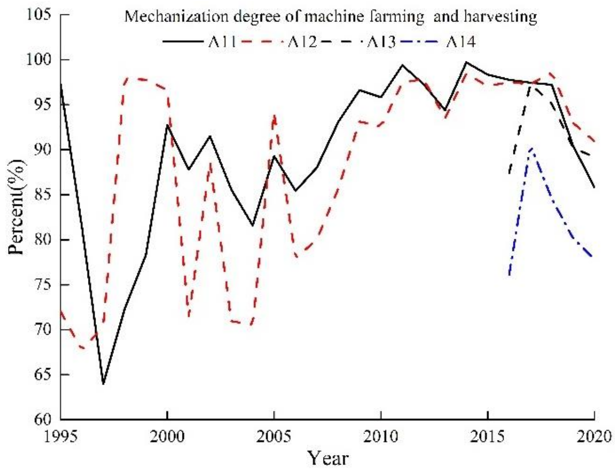

Figure 4. *Index chart for mechanization degree of farming and harvesting in Qiqihar during 1995-2020*

In terms of harvesting and plant protection, although there is no data before 2016, based on recent continuous data observations, the mechanical level of harvesting and plant protection has also reached a high level, with the maximum values reaching 90.5% and 95.15% in 2017 and 2018, respectively. The integration of unmanned agricultural aircraft has substantially enhanced the efficiency of plant protection operations. This progress is attributable to favorable national policies, the establishment of a robust operational service framework, technological advancements, and the proactive promotion of plant protection mechanization in Heilongjiang Province.

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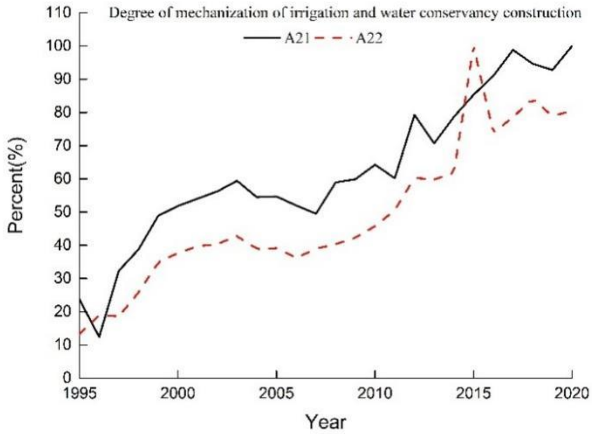

Figure 5. *Index chart for mechanization degree agricultural farmland water conservancy construction in Qiqihar during 1995-2020*

A2 accommodates two indicators as secondary indicators to reflect the degree of mechanization, water conservancy, and technological advancement of agricultural farmland water conservancy construction in the study area. The formula is as follows:

$$A2_{\,A21,\,A22,\,\varepsilon} = \sum_{i=0}^{n} \boldsymbol{a2i * A2i + \varepsilon} \tag{Eq.4}$$

In *Formula (4)*, where A21 represents the degree of irrigation mechanization and A22 represents the degree of drainage and irrigation mechanization, with weights of 60% and 40%, respectively. The specific variables are shown in *Table 2*.

Table 2. *Index of construction degree of agricultural farmland water conservancy during 1995-2020*

Variable Number	Variable Name	Variable Explanation	Variable Dimension	Maximum Value	Minimum Value	Average Value	Sample Size
A21	irrigate	Degree of irrigation mechanization	%	37.88	4.7	23.6	26
A22	Drain and irrigate	Mechanization of drainage and irrigation	%	40.88	5.4	33.17	26

An observation can be made from the data in *Table 2* and *Fig. 6* and *Fig. 7* that the degree of mechanization of agricultural water conservancy construction also shows an obvious upward trend. The lowest degree of agricultural irrigation mechanization reached 4.7%, while the highest reached 37.8%. The lowest degree of drainage and irrigation mechanization reached 5.48%, while the highest reached 40.88%. The general outlook is highly promising, although, in comparison to southern cities, the level of mechanization is somewhat lower. This is attributed to the challenging northern terrain, water scarcity, and the influence of irrigation methods and technologies. Additionally, the limited advancement in agricultural machinery water conservancy in the study area has impeded the progress of irrigation mechanization. Water scarcity prevents farmers from investing in inefficient mechanical vehicles for operation, which is still different from southern

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China. Considering that AM serves as a conduit for advanced practical technology, the study area has witnessed notable advancements in recent years. These developments encompass establishing development priorities, addressing critical technological challenges related to irrigation and drainage, developing visual measurement technology for drainage equipment, introducing concentrated farmland technology suitable for northern conditions, and implementing an intelligent system optimization model. These initiatives align with the high-standard farmland planning in the study area, which emphasizes centralized continuous cultivation, effective drought and flood management, water conservation efficiency, stable high-yield production, and ecological sustainability. These efforts have resulted in significant breakthroughs and progress.

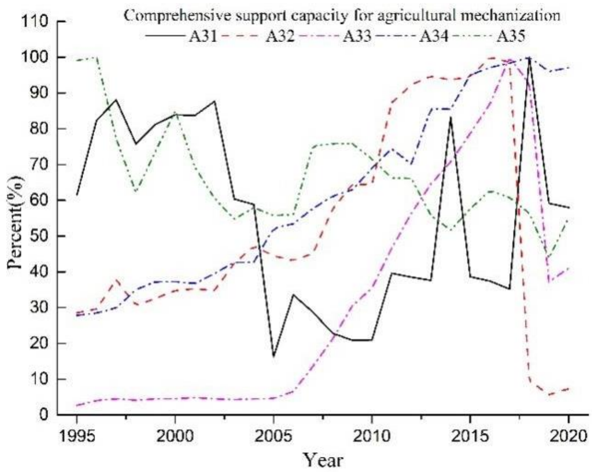

Figure 6. *Index chart of comprehensive support comprehensive capability of agricultural mechanization in Qiqihar during 1995-2020*

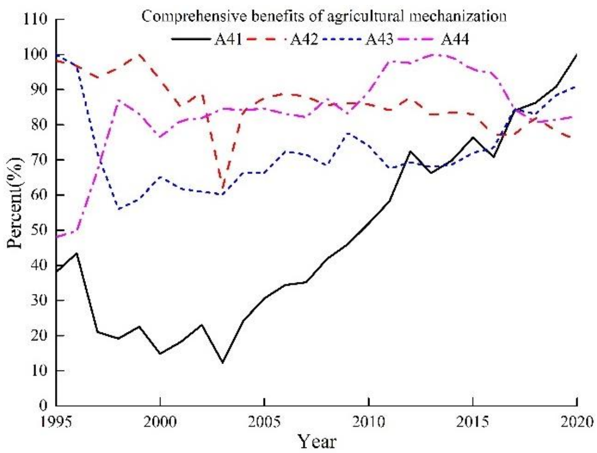

Figure 7. *AM benefit index chart in Qiqihar during 1995-2020*

A3 accommodates five indicators as secondary indicators to reflect the comprehensive security ability of AM in the study area. The formula is as follows:

$$A3_{A31,A32,A33,A34,A35,\varepsilon} = \sum_{i=0}^{n} a3i * A3i + \varepsilon \quad \text{(Eq.5)}$$

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In *Formula (5)*, A31 represents the ratio of large and medium-sized agricultural machinery equipment, with a maximum value set at 4, while A32 represents the ratio of small agricultural machinery equipment, with a maximum value set at 3. A33 represents the ratio of mechanical rice transplanters to small-scale rice transplanters (rice transplanters / small-scale rice transplanters: In view of the fact that the degree of agricultural mechanization is a comprehensive index involving multiple factors, and the ratio of mechanical rice transplanter to small rice transplanter can be used as an auxiliary index. In view of the fact that rice is also an important planting crop in the study area, this index can provide a reference for evaluating the development level of agricultural mechanization in Qiqihar region. This indicator has therefore been retained), and A34 represents the average agricultural machinery power per hectare of rice seeding area. A35 represents the proportion of agricultural technical personnel in the total number of personnel, with weights of 20%, 15%, 15%, 35%, and 15%, respectively. The specific variables are shown in *Table 3*.

Table 3. *Index of comprehensive support ability of agricultural mechanization during 1995-2020*

Variable Number	Variable Name	Variable Explanation	Variable Dimension	Maximum Value	Minimum Value	Average Value	Sample Size
A31	Large matching ratio	Large and medium-sized agricultural equipment matching ratio	%	3.09	0.59	1.709	26
A32	Small matching ratio	Small farm equipment matching ratio	%	2.76	0.16	1.44	26
A33	Rice transplanter	Mechanical ratio of motorized rice transplanter	%	31.72	0.85	10.12	26
A34	Average farm machine power	Average agricultural machine power of seeding area	megawatt	3.74	1.04	2.32	26
A35	Agricultural technician	The proportion of agricultural technicians	%	0.31	0.14	0.2	26

Through *Table 3* and *Figs. 6 and 7*, an observation can be made that during the period from 2002 to 2017, while the number of large agricultural machinery increased, there was a tendency to match with smaller agricultural machinery to adjust the imbalance between the proportion of the main unit and the matching equipment. Greater emphasis has been placed on recognizing the advantages of small agricultural machinery, known for their flexibility and adaptability, with the aim of enhancing the overall efficiency of agricultural machinery utilization. Motorized rice transplanters are a significant indicator of agricultural mechanization, and the index of rice transplanters in the study area has shown a considerably significant upward trend. This trend, when viewed from a singular perspective, underscores the remarkable enhancement of mechanization levels in this region. The proportion of agricultural technical personnel was found to be relatively small with a slight decrease, indicating that more attention needs to be paid to the training and skill improvement of agricultural technicians by governments and relevant departments

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DOI: http://dx.doi.org/10.15666/aeer/2206_53615381

to meet the development needs of modern agriculture. The study area should formulate policies tailored to its distinctive terrain, establish a robust operational service system, and leverage technological advancements. One strategy could involve strengthening collaboration among governments, enterprises, and social organizations. Additionally, there should be an expansion of training avenues and platforms, with a focus on enhancing the reach and effectiveness of agricultural practitioner training programs.

A4 accommodates four indicators as secondary indicators to reflect the comprehensive benefit of AM in the study area. The formula is as follows:

$$A4_{\,A41,\,A42,\,A43,\,A44,\,\varepsilon} = \sum_{i=0}^{n} \boldsymbol{a4i} * \boldsymbol{A4i} + \boldsymbol{\varepsilon} \quad \text{(Eq.6)}$$

In *Formula (6)*, A41 represents the agricultural labor productivity per capita (yuan), A42 represents the proportion of agricultural output value in agriculture, forestry, animal husbandry, and fisheries, A43 represents the average farmland area per capita (hectare/person), and A44 represents the proportion of agricultural labor force in the city. The weight of each indicator is 40%, 20%, 20%, and 20%, respectively. The specific variables are shown in *Table 4*.

Table 4. *Comprehensive benefit index of agricultural mechanization during 1995-2020*

Variable Number	Variable Name	Variable Explanation	Variable Dimension	Maximum Value	Minimum Value	Average Value	Sample Size
A41	Per capita output value of labor force	Per capita output value of labor force	Yuan	24497.64	3022.32	11794.5	26
A42	Proportion of agricultural output value	Proportion of agricultural output value in agriculture, forestry, husbandry and fishery	%	69.18	42.97	59.37	26
A43	Per capita planted area	Per capita planted area of agricultural labor force	Hectare Per person	1.73	0.97	1.26	26
A44	Proportion of agricultural labor force	The proportion of agricultural labor force in the city	%	37.34	17.93	31.12	26

Through the data in *Table 4* and the left chart of *Fig. 8*, an observation can be made that the four first-level indicators A1-A4 exhibited different development trends. The studied area A1 showed a slow upward trend, mainly due to the continuous increase in agricultural machinery and the continuous growth of agricultural total power, which has become a pivotal component of total agricultural production power. The ongoing accumulation has led to a comprehensive enhancement of the mechanization level in both machine tillage and machine sowing, accounting for approximately 70% of the progress. A2 showed a significant upward trend in the later stage, which is closely related to the rational use of water resources in the north and the improvement of mechanical ability, accounting for 5%. A3 presented a relatively obvious upward trend before decreasing, mainly because the farmers autonomously adopted the "scattered" planting method to

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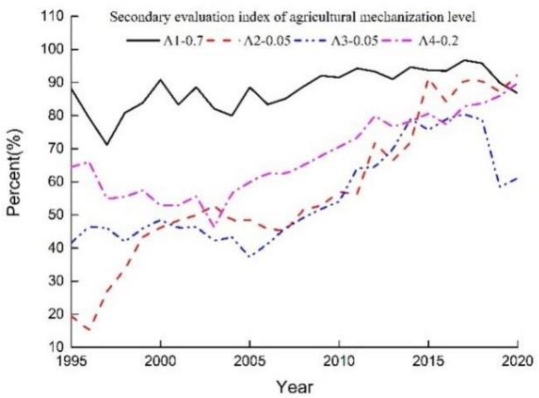
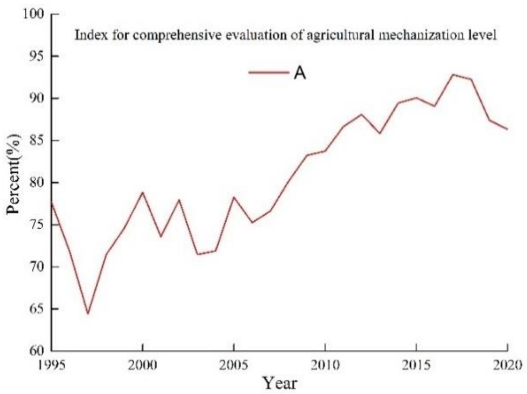
achieve a certain level of saturation, and then made autonomous adjustments, showing a more scientific and reasonable planting choice overall, accounting for 5%. A4 exhibited a slow upward trend, indicating that the comprehensive benefits of AM are gradually increasing. Farmers appeared to be experiencing more substantial incomes, and the adoption of scientific farming practices has resulted in higher returns, signifying a substantial upward trend in the overall comprehensive level of AM among farmers, contributing to about 20% of the increase. There was a close relationship between agricultural production operations and farmers' concepts, which is consistent with the significant strengthening of mechanization. A further observation can be made from the right chart of *Fig. 8* that the overall AM level in the studied area is constantly increasing. Except around 1997, China is in a critical period of economic transition, Qiqihar agricultural sector of capital investment affected by macroeconomic adjustment, coupled with backward technology and equipment, farmers concept and attitude and other factors, resulting in a reduction in investment in agricultural mechanization, which is consistent with the historical background. Overall, the AM level in the studied area was found to be relatively high, with a high popularization rate of agricultural machinery equipment, a sound agricultural machinery operation service system, an expanding area of agricultural mechanized planting, and a focus on agricultural machinery technology research and promotion. These advantages provide significant support and assurance for agricultural production in this region.



(a)



(b)

Figure 8. *Primary index and overall level evaluation index of agricultural mechanization in Qiqihar during 1995-2020*

Predictive model design for corn production potential based on climate and mechanization development levels

The Cobb-Douglas production function is widely used in economics and provides a way to quantify the relationship between factors of production (labor and capital) and output. By estimating the parameters in this function, we can understand the relative importance of different production factors in the production process and the impact of the change of production scale on the output. In addition, the function helps policy makers assess the contribution of factors such as technological progress, labor quality and capital accumulation to economic growth, so as to formulate more scientific and rational economic policies.

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The prototype function and meaning of the C-D production function are as follows:

$$PreY = A * L^\alpha * K^\beta * C^\gamma \quad \text{(Eq.7)}$$

In *Formula (7)*, PreY represents expected output, A is the efficiency coefficient, L represents labor input, K represents capital input, C represents other input factors, and α, β, and γ are the output elasticity of labor, capital, and other input factors respectively.

To make linear regression analysis easier, we usually take the logarithm of the C-D production function. Taking the logarithm of both sides of the prototype function, we get:

$$\ln(PreY)=\ln(A)+\alpha\ln(L)+\beta\ln(K)+\gamma\ln(C) \quad \text{(Eq.8)}$$

where, ln(A), α, β and γ are the parameters that need to be estimated by regression analysis.

After converting the above formula, we introduce the 8 principal component variables considered in this study. Finally, the formula for creating the C-D-AS economic-climate model is as follows:

$$\begin{gathered} \ln PreY = \beta 0+\beta 1\ln S+\beta 2\ln P+\beta 3\ln T+\beta 4\ln ACT+ \\ \beta 5\ln MTMS+\beta 6\ln FWC+\beta 7\ln CS+\beta 8\ln CB+u \end{gathered} \quad \text{(Eq.9)}$$

In *Formula (9)*, PreY, S, P, T, ACT, MTMS, FWC, CS, CB represent predicted grain yield, sunshine hours, precipitation, temperature, accumulated temperature, degree of AM for plowing and sowing, degree of agricultural water conservancy mechanization, comprehensive safeguard index, and comprehensive benefit ability index, respectively. β values represent the estimated parameters, and u represents the disturbance term. *Table 5* shows the specific data variables of the model.

Table 5. *Data variables of C-D-AS model*

Variable Number	Variable Name	Variable Explanation	Variable Dimension	Maximum Value	Minimum Value	Average Value	Sample Size
S	Sun	t	hour	3361	2416	2687.05	26
P	Precipitation	mm	millimeter	764.7	303	488.698	26
T	Temperature	degree	Degree Celsius	20.21	18	18.7906	26
ACT	Active accumulated temperature	degree	Degree Celsius	3125	2595	2816.04	26
MTMS	Machine tillage and machine sowing	Mechanization degree of machine tillage and sowing	%	89.6	73.26	83. 7	26
FWC	Farmland water conservancy	The degree of farmland water conservancy construction	%	62.68	5.93	27.43	26
CS	Comprehensive security	Degree of comprehensive support for agricultural mechanization	%	57.14	22.71	37.57	26
CB	Comprehensive benefit	Comprehensive benefits of agricultural mechanization	%	80.4	51.42	65.4	26

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Results

When analyzing the impact of climate and AMDL on grain production potential, the focus of the study was on the perspective of crop yield, and time series data from 1995 to 2020 were employed for modeling and validation. The specific results are shown in *Table 6*.

Table 6. *Results of multivariate regression analysis*

Mold		Unnormalized coefficient		Standardization coefficient	t	Collinearity statistics
		B	Standard error	Beta		VIF
R^2=0.62 D-W=1.815 Standardization 2.158	constant	3686.5	.900		2.033	
	Zscore(Sun)	499.5	.699	-.274	-.659	2.057
	Zscore(Precipitation)	845	.504	-.003	.479	2.236
	Zscore(Tempreture)	163.2	.381	.253	.544	3.091
	Zscore(ACT)	-665.4	.395	-.165	-.160	2.81
	Zscore(MTMS)	350.9	.363	.298	.415	2.928
	Zscore(FWC)	-382.5	1.728	-.339	-2.227	4.310
	Zscore(CS)	814.9	.641	.227	-.162	5.722
	Zscore(CB)	1852.1	.453	.539	3.249	6.124

From *Table 6*, an observation can be made that the dependent variable data were subject to many influencing factors, resulting in volatile changes. However, the independent variables selected in the study can explain 62.1% of the variance of the dependent variable, which is sufficient to demonstrate that the fit situation of the selected comprehensive factors met expectations. Sunshine, precipitation, temperature, MTMS, CS, and CB were found to have significant positive impacts on corn yield and form positive driving effects. Precipitation and CB had greater impacts, which further indicates that in addition to natural climate, social comprehensive benefits directly affect farmers' income and subsequently affect crop planting type selection. However, Active Tem and FWC have negative impacts and form negative driving effects. The D-W value, which is close to the critical value of 2, suggests only minor non-independence in the data, and it did not significantly affect the accuracy of the regression results. This observation can be attributed to the fact that temperature and accumulated temperature are both inherent components of the climate system. The consistent negative impact of accumulated temperature aligns with the previous findings, and there was no issue of collinearity between the variables. Additionally, the residuals conformed to a standard normal distribution, further affirming the strong alignment between the data and the model.

In this study, based on the TensorFlow platform, we adopted the gradient descent method to simulate and verify the model. Specifically, we set the iteration rate to 0.001 and the number of iterations to 5,000. During the training process, the performance of the model showed great turbulence, mainly reflected in the first 1000 iterations, and then gradually stabilized. The final result is shown in *Fig. 9*. In addition, in order to fully evaluate the performance of the model, we divided the data set into a training set and a validation set with a ratio of 0.2 to ensure that the model can show good generalization ability on different subsets.

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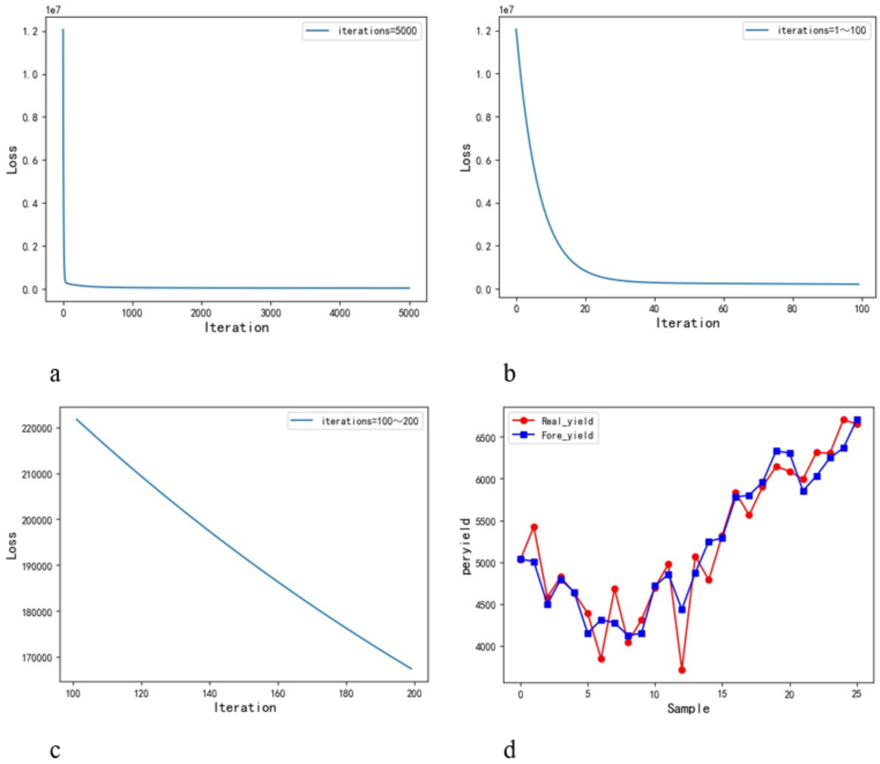

Figure 9. *Comparison of iterative process and results based on the gradient descent method*

From *Fig. 9*, an observation can be made that the correlation between predicted and actual production based on modeling with 8 independent variables was considerably high, reaching 95.3%. When compared to the analysis with 7 independent variables after removing ActiveTem, the correlation between predicted and actual production reached 94.3%. This further reinforces the significance of ActiveTem as a crucial parameter influencing crop yield, in line with previous analytical conclusions and variable selection based on practical research theory.

A detailed analysis of the potential impacts of natural climate and AMDL on grain production was conducted in the present study. However, due to the complexity and diversity of crop production processes and input factors, as well as varying production environments and natural conditions, climate and AMDL are not the only factors affecting grain production capacity. There is a need for flexible and diversified agricultural production function models. Further, when utilizing the C-D production function, a fixed ratio relationship was assumed among production factors, neglecting the influence of other factors like technological advancements and soil quality. It is essential to comprehensively incorporate these additional factors and make suitable modifications and adjustments according to real-world conditions to enhance the accuracy and reliability of the model.

Discussion

Based on our findings, it is clear that the complex interaction between natural climate variability and the level of agricultural mechanization development (AMDL) has had a significant impact on maize production in Qiqihar, Heilongjiang Province. The C-D-AS

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climate economic prediction model incorporated into the multivariable system showed a high degree of accuracy in predicting agricultural trends, with a 95.3% correlation between the predicted results and the actual data. This highlights the potential of the model as a valuable tool for policymakers and farmers in tackling the complexities of sustainable agricultural development. However, we also note that despite the model's excellent performance, the prediction accuracy in some specific environments or extreme climate conditions still needs to be improved, which points to further refinement and refinement of future research. In addition, the change in the impact of climate and AMDL on crop yields was as high as 62.1%, indicating the need for a more nuanced approach to agricultural planning and management. These insights not only contribute to a theoretical understanding of local agricultural production, but also provide practical implications for enhancing the resilience and adaptability of agricultural systems in response to changing challenges.

Conclusions

To explore the impact of climate and AMDL on crop growth potential, time series data from 1995 to 2020, data related to AMDL, and corn yield data in Qiqihar City, Heilongjiang Province were used as the basis for empirical analysis. Using the C-D production function as the theoretical foundation and the TensorFlow platform, the study established a C-D-AS economic climate production model using gradient descent method and comprehensive analysis of multiple influencing factors. The research findings show that climate and AMDL jointly affected the production capacity of grain crops, accounting for 62.1% of the variation in crop yield. The final mean squared error (MSE) was 34871, and the prediction accuracy reached 95.03%.

The present research that integrated natural and socio-economic factors to assess the production potential of food crops represents an effort to employ multivariate analysis techniques. The simulation outcomes contribute to a comprehensive understanding of the potential ramifications of climate change and the level of AM on Chinese agricultural development. The present study offers valuable empirical data and theoretical underpinnings that support agricultural modernization and sustainable development, underscoring its substantial practical significance.

Acknowledgements. This research was supported by the General Project of Basic Scientific Research Funds for Provincial Universities in Heilongjiang Province, Study on Crop Yield Change by Intelligent Analysis of Agricultural Climate Data (No. 145109142), Open Project of Heilongjiang Agricultural Multidi mensional Sensor Information Perception Engineering Technology Research Center, and Analysis and Research on Field Microclimate Based on Multidimensional Intelligent Sensing Information Cognition (No. DWCGQKF202101).

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