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Temporal Variation Analysis of Rice Yield in the Jiangsu Province, China: Application of Decision Support System for Agrotechnology Transfer Model

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ABSTRACT

The accuracy of grain yield estimation is critical for national food security. Because of the comprehensive influence of spatial differentiation conditions, such as temperature, precipitation, soil, rice variety, and irrigation, yield estimation requires integrated modeling that is based on dynamic conditions. These dynamic conditions include geographical background, biological factors, and human impact. Most existing studies focus on the observation and analysis of external factors; only a few reports on yield simulations are coupled with nature, management, and crop growth mechanism. Our study incorporates the crop growth mechanism of rice, along with data of rice varieties, soil, meteorology, and field management, to determine the rice yield in Jiangsu province, China. In addition, we have used a decision support system for the agrotechnology transfer model, along with Coupled Model Intercomparison Project data and geographic information system technology. Our results showed that: (1) A calibrated variety genetic coefficient could simulate rice biomass value (flowering stage, maturity stage, and yield) reasonably. The values of NRMSE (Normalized Root Mean Square Error) between the simulated and measured values after parameter calibration are all less than 10%, the values of d(index of agreement) are all close to 1, the simulated value of yield is in good agreement with the measured value. (2) A linear correlation between the meteorological elements and yield was observed. The linear correlation had regional differences. Notably, an increase in precipitation was conducive to the increase in yield. Except at the Huaiyin site, the other sites showed that the temperature rise could potentially lead to reduced production. We found that an increase in solar radiation was unfavorable to the production of rice in the northern and western sites in the Jiangsu province, whereas it was conducive in the southern and eastern sites. (3) Our study predicted the rice yield from typical sites in the Jiangsu province from 2019 to 2060 in the wake of climate change while excluding the extreme effects of diseases, pests, typhoons, and floods. The order of average yield per unit area is as follows: Xinghua site (8212.76 kg/ha) > Huaiyin site (7912.70 kg/ha) > Gaoyou site (7440.98 kg/ha) > Gaochun site (7512.29 kg/ha) > Ganyu site (7460.88 kg/ha) > Yixing site (7167.00 kg/ha). Notably, the average yields from the Xinghua and Huaiyin sites were higher than that from the Jiangsu province (7617.77 kg/ha). The fluctuation of the yield per unit area at each site was generally consistent with the fluctuation in the overall yield, showing a downward trend and tends to be stable. The dispersion of yield per unit area indicates that Gaochun had the most stable yield per unit area followed by Xinghua, Ganyu, Yixing, Huaiyin, and Gaoyou. The yield per unit area of the Huaiyin and Gaoyou sites was unstable and portrayed the biggest fluctuations. Future studies need to focus on how to deal with spatial variation and carry out adaptive verification to make the simulation results applicable to more dimensions.

1. Introduction

Food-related issues are deemed as the top priority of agricultural production. Obtaining accurate crop growth monitoring information and yield prediction information in real-time is crucial for agricultural management and food security [1]. Currently, China is facing many issues regarding cultivated land, including less cultivated land per capita, poor quality and serious degradation of cultivated land, the severe shortage of reserved cultivated land resources, and aggravation of cultivated land reduction [2]. Crop yield is a direct index that can be used to evaluate farmland productivity and income of farmers. Timely and effective estimation and prediction of crop yield per unit area can aid in decision-making at the national level and offer guidance to farmers (with respect to grain storage and grain trading), contributing considerably to national agricultural decision-making, farmland production management, and grain storage security [1, 3]. Therefore, studies on crop yield estimation have become an essential topic in many disciplines, including geography and agronomy. Affected by many factors, such as meteorology, soil, varieties, and cultivation management measures, the farmland production system has significant temporal and spatial variability, and several urgent problems in determining crop yield remain unsolved. First, it is imperative to develop an integrated model that is based on nature, humanities, biotechnology, and other factors to predict the trend of agricultural production. Second, we need to quantify the impact of these factors on agricultural production. To solve these problems, it is critical to understand the complex process of crop yield formation, along with its physiology and biochemistry. From the perspective of multiple influencing factors, such as meteorological conditions, soil conditions, field management, and phenological and agricultural time information, ensuring the rationality and accuracy of yield per unit area estimation also play an important role [3]. All these solutions serve as an important reference for governments at all levels to formulate efficient policies and guidelines related to food security, with both practical and theoretical innovation [4].

In recent years, satellite remote sensing and crop growth models have been widely applied for crop growth monitoring and yield prediction. Applying remote sensing technology for yield estimation is one of the earliest agricultural remote sensing applications [5]. Wang put forward the concepts of “relative spectral variable” and “relative yield” to carry out the multi-period relative variable rice unmanned aerial vehicle remote sensing yield estimation [6]. Quarmay *et al*. estimated the total yield of wheat, corn, and rice using the cumulative normalized difference vegetation index (NDVI) calculated by multi-temporal AVHRR(advanced very high-resolution radiometer) data [7]. Wang *et al*. used the NDVI and enhanced vegetation index derived from the moderate resolution imaging spectroradiometer dataset to predict the winter wheat yield in the United States of America using linear models [8]. Although it is operable and concise to quantitatively obtain the key physical and chemical parameters related to crop growth by using remote sensing data to estimate the crop yield in the current season, it can not really reveal the impact of the internal mechanism affecting rice yield change, and the yield change caused by the impact of climate change on crops in the future can not be obtained only through remote sensing inversion, The scalability of space-time application is not strong. Additionally, the alterations in yield caused by the impact of climate change on crops in the future cannot be obtained through remote sensing inversion Which causes the lack of scalability in spatio-temporal applications, and therefore, remote sensing technology can integrate into a crop growth model for complementary advantages [5].

The aim of applying the crop growth model for crop yield estimation is to predict the expected crop yield and identify the spatiotemporal distribution and change rules of crop yield, based on the crop physiology and ecology and the comprehensive influence of geographical environmental factors, including temperature, precipitation, soil, regional differences, rice varieties, and anthropological factors [9, 10]. Combined with the advantages of remote sensing in parameter acquisition, the crop yield estimation model has evolved from simple parameter statistics to yield estimation systems based on physiological and ecological mechanisms [11–13], its rapid development provides quantitative tools for crop growth and yield prediction, climate, variety, and management measure effect evaluation. Major breakthroughs have been made in the most accurate large-scale and field-level yield estimations. In addition, with the help of daily meteorological data collected in the past years, the crop model can cover various climatic year types and obtain the crop yield potential under different climatic year types [14-16]. As a supplement to the field experiment research method, crop models have an increasingly extensive application. They play an important role in cultivation and breeding, field management, yield prediction, disaster assessment, and agricultural technology popularization. However, because of the complexity and large parameter differences of various models developed in the world, the application and popularization of the models have a few challenges. To solve this problem, various models have been standardized in the USA to form a comprehensive decision support system for agrotechnology transfer (DSSAT) system, which can analyze the impact of agricultural technology worldwide on soil, crop growth, and development. The DSSAT system encompasses many series of models, including CERES (crop environment resource synthesis) and CROPGRO (Crop GROwth). The cereal crop simulation model CERES is most widely used for studying the impact of climate change on agriculture. It can simulate the growth, development, and yield of rice according to the interaction between soil, water, weather, atmosphere, and the crop itself, along with field management. CERES has developed different yield estimation models, including CERES-Maize, CERES-Wheat, and CERES-Rice [17-20]. Bhatia *et al*. applied the DSSAT model to analyze the potential yields of soybean with water limitation and non-limitation in India during 2008 [21]. The DSSAT model was also used to study the impact of future climate change and irrigation demand on crops to provide strategies in response to the future climate change [22-25]. In our study, the DSSAT model was combined with geographic information system (GIS) to predict the spatiotemporal variation of crop yield with climate and management changes. Our aim was to mitigate the risk of reduced yield [26, 27]. The CERES-Rice model has been established to estimate rice biomass and yield accurately. In particular, the model was increasingly used to evaluate the impact of climate change on rice production after the 1990s.

In this study, we used the DSSAT crop yield estimation model. The influences of extreme abnormal weather were excluded. From the perspective of physiological and ecological mechanisms of crops, our study considered the influencing factors of crop growth, including field management and rice genetic coefficient, along with natural conditions. Six typical paddy rice planting sites in the Jiangsu province, China, were selected as the study area. After calibrating the genetic factors of rice varieties at each site, we simulated the rice yield per unit area of the main planting sites in the Jiangsu province from 1990 to 2018 and verified the accuracy of the simulated yield. Under the condition that the relative difference (NRMSE) and coincidence(d) between simulated and observed values are good, the yield simulation is carried out by using the calibration results of rice genetic factors. This study combined the calibrated rice genetic factors with the Coupled Model Intercomparison Project (CMIP)5 climate prediction downscaling dataset of the sites during 2019–2060 and predicted the rice yield per unit area of the rice plantation sites in the Jiangsu province for the next 41 years. Our study may provide a reliable decision-making reference for realizing the rational utilization of cultivated land resources, optimization of rice production space layout, and establishment of food security mechanisms in Jiangsu province.

2. Materials and Methods

2.1. Overview of the Study Area

Jiangsu province is located in the middle and lower reaches of the Yangtze River in China, (116° 18′ E-121° 57′ E, 30° 45′ N-35° 20′ N). Jiangsu is bordered by Shandong in the north, the Yellow Sea in the east, Zhejiang, and Shanghai in the southeast, and Anhui in the west. It has a total of 13 prefecture-level cities (Fig. **1**). Located in the cross-junction of China's economic "T- shaped" overall layout, the core area of the Yangtze river delta and the North–South cultural transition zone, Jiangsu has a favorable geographical location.

With an area of 103229.17 km^2, Jiangsu is the province with the lowest elevation terrain in China. It is covered predominantly by plains and most areas are below 50 m above the sea level, the plain area accounts for 86.89%. Jiangsu is located in a transitional climate region (from temperate to subtropical zone), with a mild climate, moderate rainfall, and distinct four seasons. The average temperature in Jiangsu is 13-16 ℃. The annual rainfall runoff-depth is between 150 and 400 mm, resulting in abundant underground water sources. Jiangsu is one of the main and high-yield rice provinces in China. Both the total yield and planting area rank first in China. Jiangsu only has single-cropping rice, with medium-grained rice grown in the north region of the Yangtze River Basin and late rice grown in the south region of the Yangtze River Basin. Drawing upon the zoning method of Zhang *et al*., [28] in our study, we divided Jiangsu into four regions that cultivated different rice varieties (Fig. **1**).

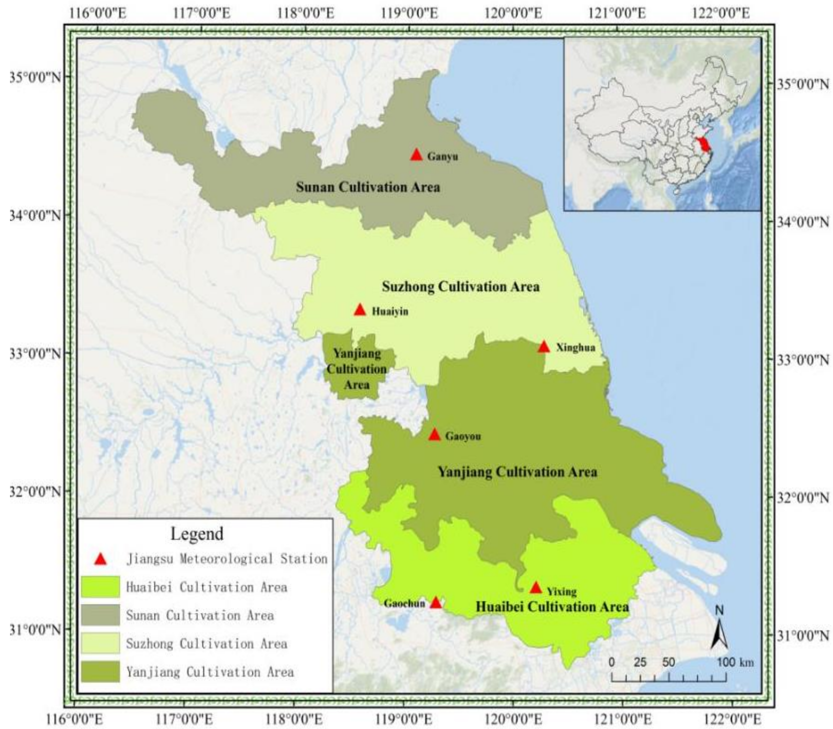

Figure 1: Research area of Jiangsu province.

2.2. Data Sources

The data used in this study included Jiangsu's basic geographic data (obtained from the administrative division), a digital elevation model (DEM), observation data from Jiangsu meteorological sites and its data description documents, downscaled climate projections from the CMIP dataset, and socio-economic statistics, along with land use (vector), soil, and phenological data.

2.3. DSSAT Yield Projection Model

An accurate estimation of the annual rice yield in the Jiangsu province is based on long-time series rice yield simulation prediction and spatiotemporal analysis. The four main rice-growing areas in the Jiangsu province were selected in this study. The influence of extreme abnormal weather factors was excluded. We conducted the regional calibration of the rice genetic coefficient in each area using random sampling observation data of yield from 1990 to 2018. Thereafter, the multi-factor parameters, such as meteorology, soil, field management, and modified genetic coefficient were comprehensively considered. Then, we used the DSSAT rice yield estimation model to estimate the change in rice yield per unit area from 1990 to 2018 in the Jiangsu province. After comparing the simulated value with the observed value and verifying the rationality of the model, the long-time series simulation prediction of rice yield per unit area in the typical rice planting sites in the Jiangsu province was carried out using the multi-year CMIP5 downscaled climate projection dataset from 2019 to 2060.

2.3.1. Model Parameter Pretreatment

Meteorological Parameters

The DSSAT model considered the daily data, and the daily meteorological documents were needed for simulating crop growth (from sowing to maturity). Concurrently, for the model to evaluate the external natural conditions during the simulation period more accurately and improve the rationality of the model simulation, we incorporated the meteorological data before crop sowing and after the harvest. The meteorological data included the name of the meteorological site, country name, longitude and latitude, altitude, daily solar radiation (MJ/m^2), daily maximum temperature (℃), daily minimum temperature (℃), and daily precipitation (mm).

The redundant data (e.g., null and missing measurement) not required by the DSSAT model in the original meteorological data were preprocessed by batch processing the meteorological data. The meteorological data were first processed according to the rules described in Table **2** and the actual element values of the meteorological factors were obtained.

Table 1: Research data.

Data	Sources
Land use data (2015)	Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences (CAS)
DEM data (30 m)	
Daily observed meteorological data from 1990 to 2018 (precipitation, daily maximum temperature, daily minimum temperature, and solar radiation)	
Soil type data	Institute of Soil Science, CAS Data of the second soil survey in China
1:4,000,000 soil nutrient data	Soil Center, National Earth System Science Data Center
CMIP5 downscaling climate projections dataset	China crop model computing service
Socio-economic statistics (Field management data, e.g., actual yield per unit area and rice fertilization)	Statistical Communiqué of the People's Republic of China on the National Economic and Social Development Jiangsu Statistical Yearbook and other literature
Phenological data of rice growth and development	China's social-economic big data research platform

*Note: digital elevation model (DEM).

Table 2: Description table of meteorological data attributes.

Data Eigen Value	Note	Calibrated Value
32744	Blank	NULL
32700	Microscale	0
32766	Missing measurement	NULL
31XXX	Snow (sleet, snowstorm) XXX denotes precipitation	XXX
30XXX	Rain and snow XXX denotes precipitation	XXX
32XXX	Fog dew frost XXX denotes precipitation	XXX

Because it is impossible to directly observe the solar radiation factor required by the model, our study refered to the formula for calculating short wave radiation using the FAO Penman-Monteith method [9, 29, 30] (Eqs. 1–6), which converts the daily sunshine hours recorded in the meteorological data to daily radiation value, as follows:

$$R_s = (a_s + b_s \frac{n}{N})R_a \tag{1}$$

$$R_a = \frac{24(60)}{\pi} G_{sc} d_r [\omega_s \, sin(\varphi) \, sin(\delta) + cos\,(\varphi) cos\,(\delta) sin\,(\omega_s)] \tag{2}$$

$$N = \frac{24}{\pi}\omega_s \tag{3}$$

$$\omega_s = arccos[-tan\,(\varphi) tan\,(\delta)] \tag{4}$$

$$d_r = 1 + 0.033 cos\,(\frac{2\pi}{365} J) \tag{5}$$

$$\delta = 0.409 sin\,(\frac{2\pi}{365} J - 1.39) \tag{6}$$

Where R_s is short wave radiation (MJ/m^2 per day), n refers to the actual sunshine hours (h), N is the maximum possible sunshine hours (h), n/N is relative sunshine, and G_{sc} is the solar constant number (0.0820 MJ/m^2 per minute), R_a denotes extraterrestrial radiation ($MJm^{-2}day^{-1}$), a_s and b_s are regression constant, representing the transmission coefficient of extraterrestrial radiation reaching the earth's surface [on cloudy days ($n = 0$) and sunny days ($n = N$)], $a_s + b_s$ refers to the transmittance of extraterrestrial radiation reaching the earth's surface, d_r is the relative distance between the sun and the earth, φ is the latitude (rad), δ is the sun inclination angle, ω_s is the sunset angle, J is the day sequence, and π = 3.14159. The calculation result (R_s) is the required daily solar radiation.

Soil Parameters

Soil is the basis of crop growth. The model requires accurate soil data to ensure the rationality of simulation results. The operation of the DSSAT model needs to input the corresponding soil information of each site, including data such as soil type, nutrient, and profile (physical, chemical, and morphological properties of surface and stratification; Table **3**), which is used to simulate the moisture content of the soil, carbon and nitrogen nutrient cycle, and root growth. Soil taxonomy consists of soil order, soil group and subgroup, soil genus, soil type, and soil varieties. The profile information of soil species or varieties in soil taxonomy was input in the experiments. Table **4** shows the soil species of each site.

Table 3: Description of the physical, chemical, and morphological properties of soil surface and stratification.

Soil Type	Soil Properties	Impacting Factors
Soil surface	Soil type, color, slope, permeability, reflectance	Reflects the effects of soil water infiltration, evaporation, drainage, nutrients, and other factors on crop yield
	Soil thickness	
	Soil moisture evaporation limit (mm)	
	Number of runoff curves and soil drainage rate ($\mathrm{fraction/day}$)	
	Photosynthetic factors (0–1)	
Soil stratification	Lower limit of soil water or moisture content at withering point ($\mathrm{cm^3 \cdot cm^{-3}}$)	
	Field moisture capacity ($\mathrm{cm^3 \cdot cm^{-3}}$)	
	Saturated moisture content ($\mathrm{cm^3 \cdot cm^{-3}}$)	
	Soil bulk density ($\mathrm{g \cdot cm^{-3}}$)	
	Soil organic carbon	
	Nitrogen（$\mathrm{wt.\%}$）	
	Soil pH	
	Clay content ($\mathrm{wt.\% < 0.002mm\ soil\ particle-size}$) Powder content（$\mathrm{wt.\%0.002-0.05mm\ particle-size}$）	

Table 4: Information of soil species in the rice-cultivating sites.

City	County	Site Code	Meteorological Site	Soil Type	Longitude (°)	Latitude (°)	Elevation (m)
Lianyugang	Ganyu	LYGY	58040	Silt at sand bottom	119.08	34.51	10.8
Huai'an	Huaiyin	HAHY	58143	Silt at sand bottom	119.51	33.48	6.1
Taizhou	Xinghua	TZXH	58158	Ground clay	120.29	33.12	7.1
Zhenjiang	Gaoyou	ZJZJ	58241	Yellow soil	119.27	32.48	9.6
Nanjing	Gaochun	NJGC	58345	Green soil at sand bottom	119.29	31.26	8.1
Wuxi	Yixing	WXYX	58354	Clay head	120.21	31.37	4.1

Field Experiment Parameters

The field management data of DSSAT model includes the name and number of field experiments, experiment treatment, soil type information, phenological information (crop sowing and harvest etc.), irrigation date and volume, fertilization type, date, and amount. The null data and abnormalities in the required data were corrected and improved by using the mean value of adjacent years.

Rice Planting Monitoring Site

The operation of DSSAT model requires information on rice variety, experimental data, agricultural site location, and other agricultural data. We selected six rice-cultivating sites that have relatively complete data and are evenly distributed in the Jiangsu rice-growing area. The original agricultural data of different years were sorted, summarized, and stored. In addition, ArcGIS was used to process the coordinate information of sites, such as projection change and coordinate transformation, which was used for registration, geometric correction, and digitization with the administrative division map of Jiangsu province.

2.3.2. Variety Parameter Debugging and Verification

The various parameters of DSSAT model controlling crop growth were stored in variety parameter (.CUL), species parameter (.SPE), and ecological parameter (.ECO) files. User-adjustable parameters were stored in the species parameter file. These parameters were used in the DSSAT model to simulate crop growth and development and yield formation. The genetic parameters of varieties were adjusted by trial and error until the optimal consistency between the simulation value output was obtained using the adjustment parameters and the measured value.

Generally, the genetic parameters of rice in a certain range of planting areas do not change with time and space. Therefore, we assumed that the genetic parameters of rice varieties in the four rice-growing areas of the Jiangsu province were the same. Debugging and verification were conducted on the genetic parameters of rice varieties in the four rice-growing areas, including (1) Single point debugging: The annual rice variety parameter experimental data of each site was input into the model to simulate the average genetic parameters of the same variety for many years; (2) Variety debugging: A comprehensive simulation was performed on the same variety in each rice-cropping area to determine the optimal genetic parameters of varieties in each area; and (3) Effect calibration: The rice growth under different temporal and spatial conditions was simulated to compare errors between the model simulation value and actual observation value. A cyclic debugging was conducted to improve the localized simulation effect of the model.

The description of each rice variety was composed of genetic parameter codes and parameter values. The rice varieties in the model were determined using eight genetic parameter values, as shown in Table **5**.

Table 5: Description of genetic parameters of crop varieties.

Genetic Parameters	Definition	Note
P1	Heat hours required to complete the basic vegetative growth period (℃/d)	Parameters related to development
P2O	Optimum photoperiod (H)	
P2R	The delayed degree of flower bud differentiation P2R caused by each day longer than the optimal photoperiod for 1h (℃/d)	
P5	Heat hour required to complete grouting period P5 (℃/d)	
G1	Coefficient of potential spikelets numbers (expressed in spikelets per gram of dry matter weight of main stem at flowering)	Parameters related to yield
G2	Potential grain weight G2 (g)	
G3	Tillering coefficient G3 (relative value, taking the tillering capacity of rice variety IR64 under ideal environment as 1.0)	
G4	Temperature tolerance coefficient G4 (relative value, 1.0 for varieties grown in conventional environment)	

The determination of the eight genetic parameters required the data of single-site meteorology, soil, and field management, which were treated as the initial values of the genetic parameters and input the model for cyclic debugging. Thereafter, a set of optimal genetic parameters were determined for each rice variety.

We used R^2 to judge the goodness of fit between the simulated value and the observed value which expresses the fitting degree of the regression line, After re-study and discussion, the author decided to use Root Mean Square Error (RMSE) and Normalized Root Mean Square Error (NRMSE) to measure the relative difference between simulated and measured values when testing the applicability of the model. The consistency index d (index of agreement) is used to check the consistency between the simulated value and the measured value. The calculation method is shown in formulas (1), (2) and (3).

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(S_i - R_i)^2}{n}} \tag{1}$$

$$\mathrm{NRMSE} = \frac{\mathrm{RMSE}}{\bar{R}} \times 100\% \tag{2}$$

$$d = 1 - \left[\frac{\sum_{i=1}^{n}(S_i - R_i)^2}{\sum_{i=1}^{n}(|S_i'| - |R_i'|)^2}\right] \tag{3}$$

In the formula, S_i is the simulated value, R_i is the measured value, $S_i^{'} = S_i - \bar{R}$, $R_i^{'} = R_i - \bar{R}$, $\bar{R}$ is the average value of the measured value, and n is the number of samples of the simulated value. It is generally believed that, $NRMSE < 10\%$ is excellent; $10\% < NRMSE < 20\%$ is good; $20\% < NRMSE < 30\%$ is medium; $NRMSE > 30\%$ is poor. The closer the value of d is to 1, the better the consistency between the simulated value and the measured value, otherwise it is the opposite.

2.3.3. Simulation and Prediction of Rice Yield

Rice yield changes correlate with spatiotemporal and regional changes. Using time as a measuring unit, we conducted a long-time series prediction on the rice yield at each of the six sites in the Jiangsu province and analyzed its distribution rules and variation features. Under the condition of ensuring the rationality of the simulated value, we used the meteorological data of RCP4.5 medium and low greenhouse gas (GHG) emission and radiation forcing scenarios derived from the CMIP5 climate prediction downscaling dataset. In addition, assuming that the soil conditions, field management, and other factors remain unchanged in the future, we employed the DSSAT model to simulate and predict the yield per unit area of six typical rice sites in the Jiangsu province from 2019 to 2060. The corresponding data was analyzed. The abnormalities in the data are caused by the impact of extreme weather and other factors on rice yield. Other data were processed drawing upon previous studies [3, 15, 16]. Based on the simulated annual rice yield from 2019 to 2060, the average yield of each site from 2019 to 2029, 2030 to 2039, 2040 to 2049, and 2050 to 2060 were calculated.

3. Results

3.1. Correction of Rice Variety Parameters

We collected random sampling data of rice varieties (flowering stage, maturity stage, and yield) from six typical sites in the Jiangsu province from 1990 to 2018 to debug and determine the optimal genetic parameters of the crop. A better goodness-of-fit (R^2) of the flowering stage, maturity stage, and yield after genetic parameter calibration was obtained than that before calibration (Fig. **2**). By comparing and analyzing the simulated and measured values after parameter calibration (Table **6**), the result shows that the values of NRMSE are all less than 10%, the values of d are all close to 1, the simulated value of yield is in good agreement with the measured value. It shows that various parameters can accurately reflect the main genetic characteristics of crop varieties, and can be used to simulate crop production potential. The rice variety genetic parameters after calibration are shown in Table **7**.

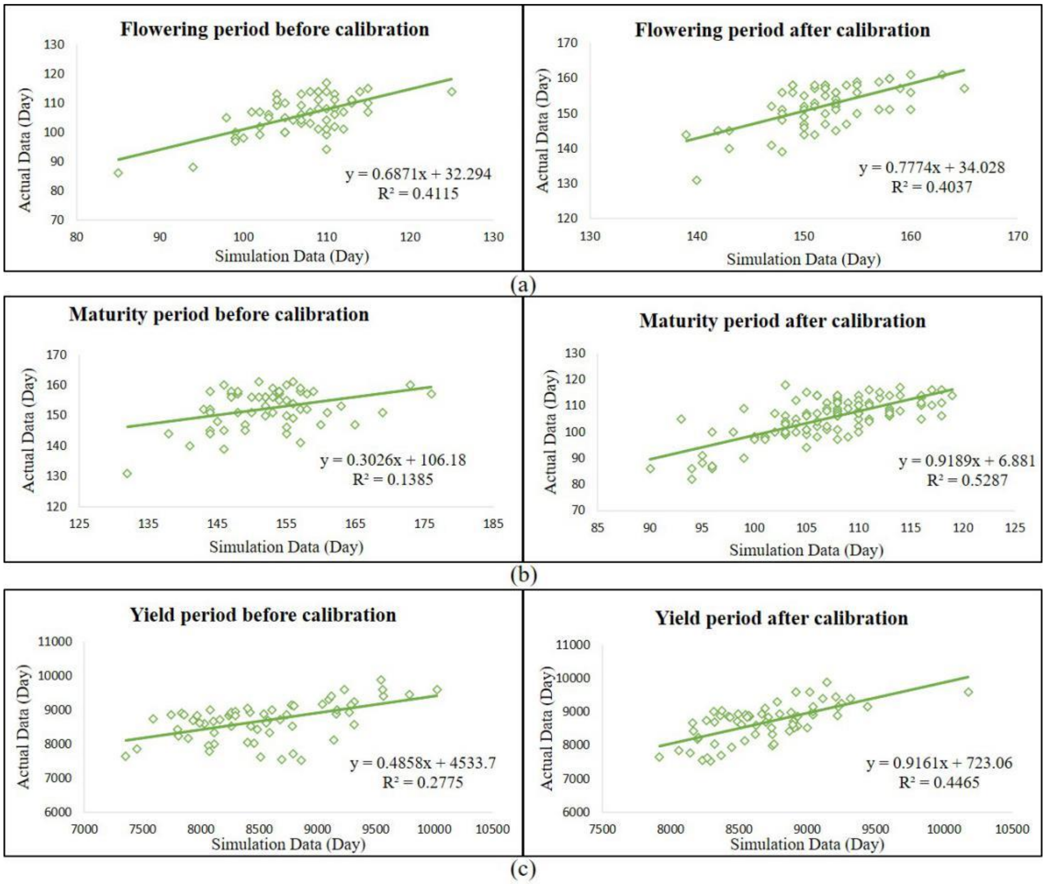

Figure 2: Debugging and calibration of rice genetic parameters. Parameter calibration of flowering (a), maturity (b) and yield (c).

Table 6: Error comparison between simulated and measured rice yield in Jiangsu Province.

Parameter / Index	Flowering Period	Maturity Period	Yield
NRMSE	0.14%	1.69%	0.07%
d	0.9149	0.9983	0.9998

Table 7: Genetic parameter after calibration of rice varieties.

Parameter Name		P1	P2R	P5	P2O	G1	G2	G3	G4
Site code	HAHY (Huai'yin site)	720.0	170.0	450.0	12.60	50.0	0.0190	1.00	1.00
	LYGY (Ganyu site)	770.0	150.0	490.0	13.20	50.0	0.0190	1.00	0.90
	TZXH (Xinghua site)	580.0	162.0	490.0	12.20	60.0	0.0190	1.00	1.00
	ZJGY (Gaoyou site)	680.0	170.0	490.0	12.00	49.0	0.0190	1.00	1.00
	NJGC (Gaochun site)	750.0	190.0	490.0	12.00	48.0	0.0200	1.00	1.00
	WXYX (Yixing site)	750.0	220.0	558.0	12.7	67.0	0.0150	1.00	1.00

3.2. Verification and Analysis of Historical Rice Yield Simulation Results

The DSSAT model was run based on the databases of meteorology, soil, field management, and a variety of genetic parameters. We also used ArcGIS for correlation, operation, and format conversion to obtain the annual rice yield simulated data from 1990 to 2018. The simulated value was compared with the measured value to verify the accuracy of the model simulation results.

The actual rice yield per unit area of each site was treated as a reference, excluding the year of missing statistical data. Fig. **3** demonstrates the comparison between the simulated and measured values. A small statistical error was observed between the simulated and measured values, and the overall change trend of the simulation was consistent with that of the actual observation, thus meeting the experimental requirements.

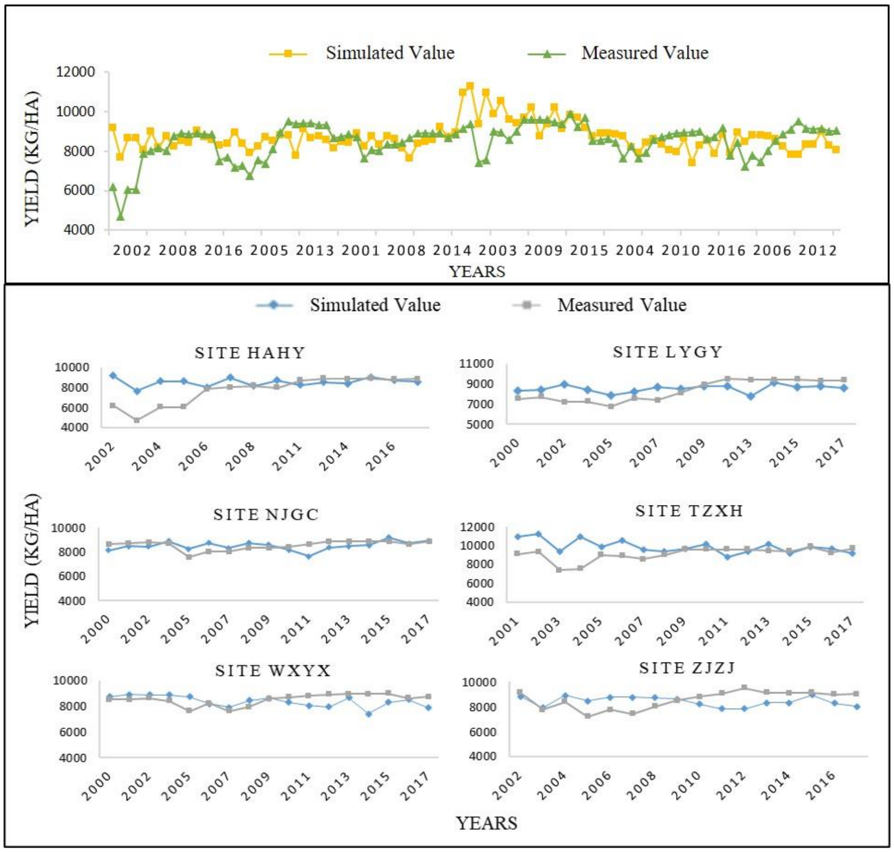

Figure 3: Comparison of simulated and measured values of rice yield.

3.3. Response Analysis of Rice Yield to Meteorological Factors

Fig. **4** shows the comparison and analysis of the daily value data of four meteorological elements and the annual rice production data of each site. The difference in rainfall between the years was the most evident, but it is difficult to identify the relationship between meteorological elements and rice yield based on the change of daily value data. Therefore, this study sorted the data of the annual total accumulated temperature, maximum precipitation, minimum precipitation, and solar radiation during the rice growth stage in the past years (1990-2018).

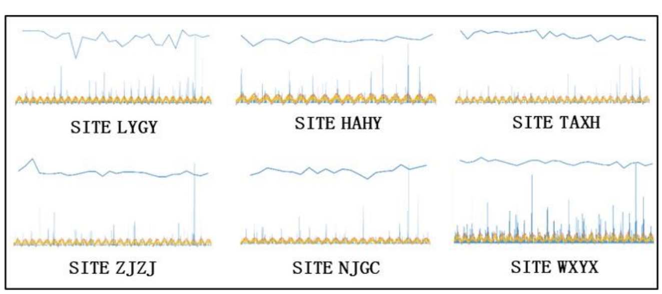

Figure 4: Comparison and analysis of meteorological factors and rice yield.

3.3.1. Response Analysis of Rice Yield to Rainfall

A great difference in rainfall was observed for different years and regions. The trend line in the scatter plot of rice yield-total precipitation in the growth stage of each site showed an upward trend. Thus, a positive correlation existed between rice yield and total precipitation in the growth stage, indicating that the increase of precipitation in the growth stage was conducive to the increase of rice yield.

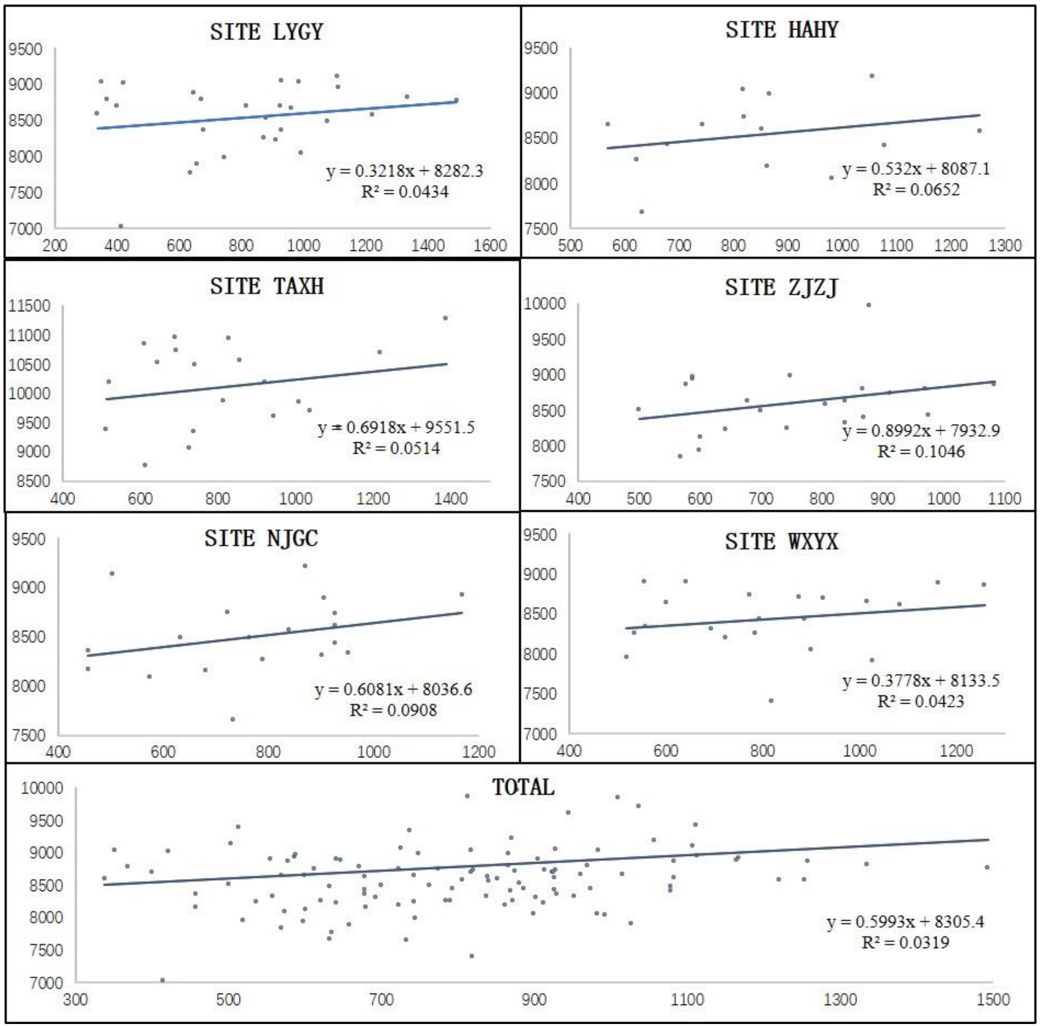

Figure 5: Representation of the correlation analysis of rainfall and rice yield.

3.3.2. Response Analysis of Rice Yield to Temperature

Except for the highest/low temperature of the HAHY site and the highest temperature of NJGC site, a negative correlation was observed between the overall rice yield of other sites and the total rice yield of Jiangsu province and the (highest/low) accumulated temperature during the growth period, indicating that the increase in temperature during the growth period of rice would result in a decrease in the rice yield.

3.3.3. Response Analysis of Rice Yield to Solar Radiation

Each site had different correlations between rice yield and total solar radiation during the growth period. Among them, the rice yields of the LYGY, HAHY, and ZJZJ sites showed a negative correlation with the total solar radiation value, and a positive correlation was reported between the rice yield of the TZXH, NJGC, and WXYX sites and the overall rice yield of Jiangsu and the total solar radiation value. This indicates that the increase of solar radiation during the growth generated two sides of effects on rice yield, and the overall effect was positive.

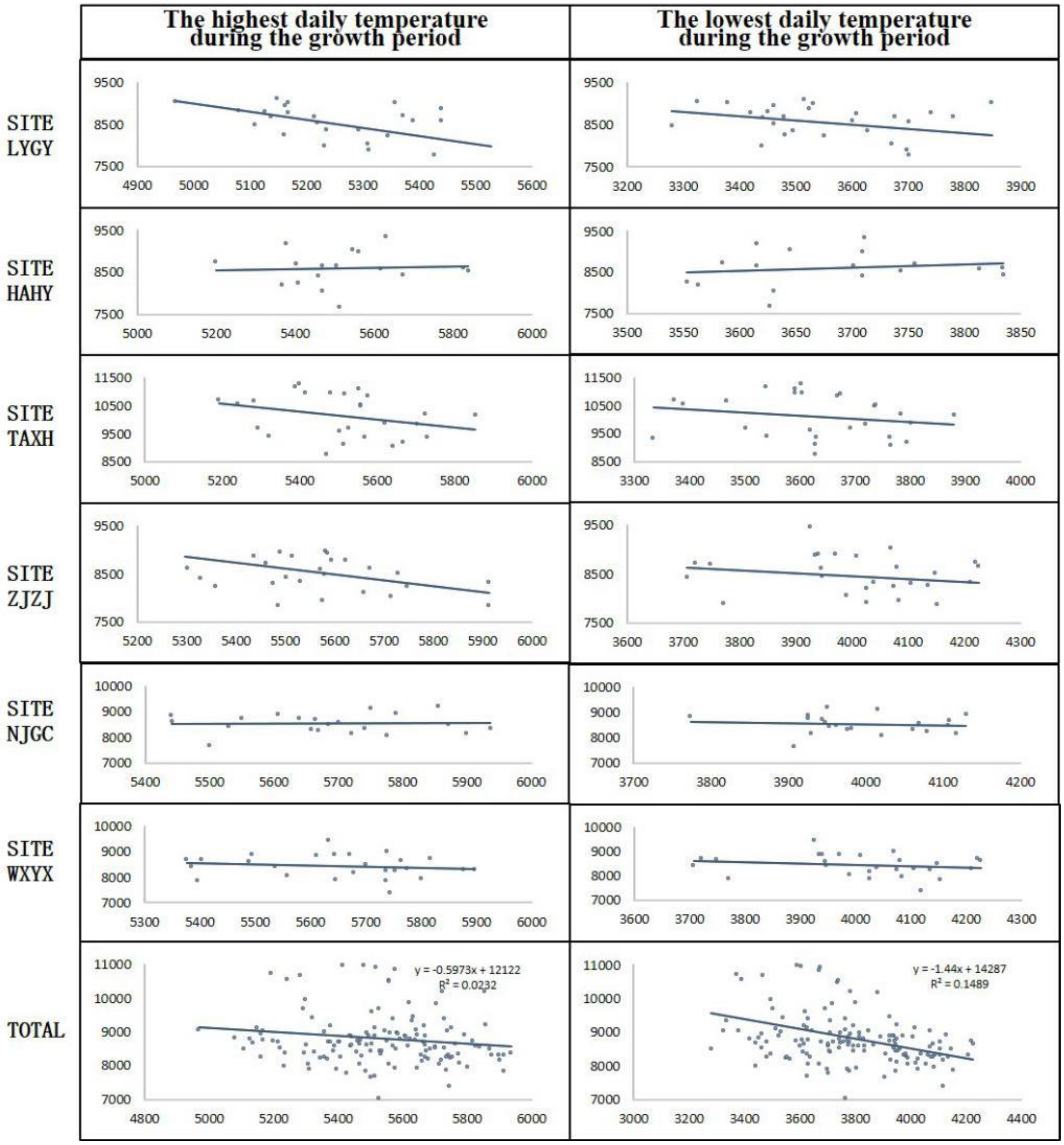

Figure 6: Representation of the correlation analysis of temperature and rice yield.

3.3.4. Multiple Linear Regression Analysis between Rice Yield and Meteorological Elements

We conducted a multiple linear regression analysis, based on the average annual values of meteorological factors and annual yield data of six sites in the Jiangsu province during the rice growth stages from 1990 to 2018. The purpose was to study the linear regression relationship between rice yield and meteorological factors in Jiangsu province. The regression analysis results are shown in Table **8**. The multiple linear regression equation was

$$\mathrm{y} = 0.0332x_1 - 1.2647x_2 - 1.1644x_3 + 1.1687x_4 + 16330.9738.$$

Table 8: Multiple linear regression analysis results.

Parameters	Total Precipitation (mm)	Total Highest Temperature (℃)	Total Lowest Temperature (℃)	Total Solar Radiation (MJ/m²)	Constant
Variable coefficient	x_1	x_2	x_3	x_4	b
	0.0332	-1.2647	-1.1644	1.1687	16330.9738

The R^2 obtained by regression statistics reached 0.66 and significance statistics was 0.0079, less than the significant level 0.05, indicating a significant regression effect of the regression equation. The following findings were concluded from the regression analysis:

(1) A positive correlation was observed between rice yield and the total precipitation in the growth period. An appropriate increase of precipitation was conducive to increasing the total rice yield, but short-term heavy precipitation events could pose a great threat to rice production. (2) There was a negative correlation between rice yield and temperature. In the event of low temperature, temperature rise increased the rice yield. However, if the temperature increase exceeded the appropriate range, the rice yield was reduced. (3) A positive correlation was seen between rice yield and solar radiation during the growth stage of rice.

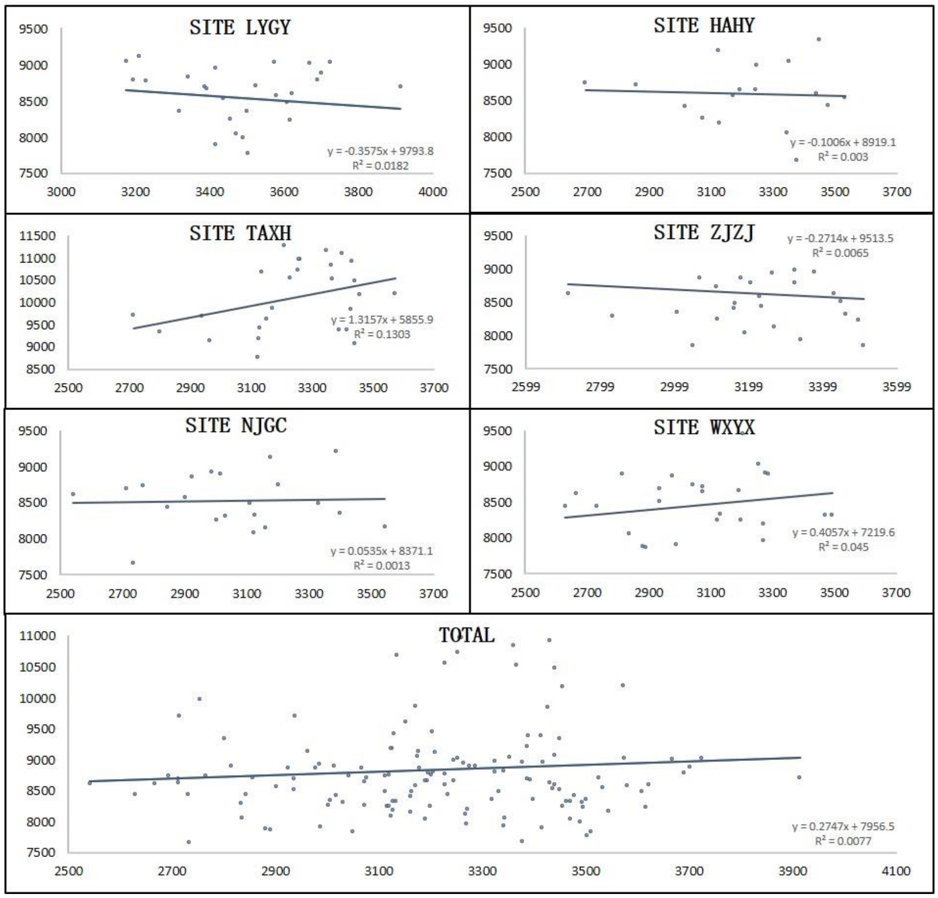

Figure 7: Representation of the correlation analysis of solar radiation and rice yield.

3.4. Simulation and Prediction of Rice Yield in the Wake of Future Climate Change

The results showed that the DSSAT modeling conducted parameter debugging by evaluating the simulation results of critical growth, development stages, and yield (such as rice flowering and maturity). The values of NRMSE between the simulated and measured values after parameter calibration are all less than 10%, the values of d are all close to 1, the simulated value of yield is in good agreement with the measured value. The average yield of each site from 2019 to 2029, 2030 to 2039, 2040 to 2049, and 2050 to 2060 were spatially presented (Fig. **8**). We can see, a small difference was observed in the yield per unit area value of each year period at the same site, and the overall situation was relatively stable.

According to the data in table **9**, which portrays the average yield per unit area of the six sites. Xinghua had the highest average yield per unit area followed by the other five sites (Xinghua > Huaiyin > Gaochun > Ganyu > Gaoyou > Yixing). Yixing had the lowest average yield per unit area. Xinghua (8212.76 kg/ha) and Huaiyin (7912.70 kg/ha) had a higher average yield per unit area than the average level (7617.77 kg/ha), whereas Gaoyou (7440.98

kg/ha), Gaochun (7512.29 kg/ha), Ganyu (7460.88 kg/ha), and Yixing (7167.00 kg/ha) had a lower average yield per unit area than the average level.

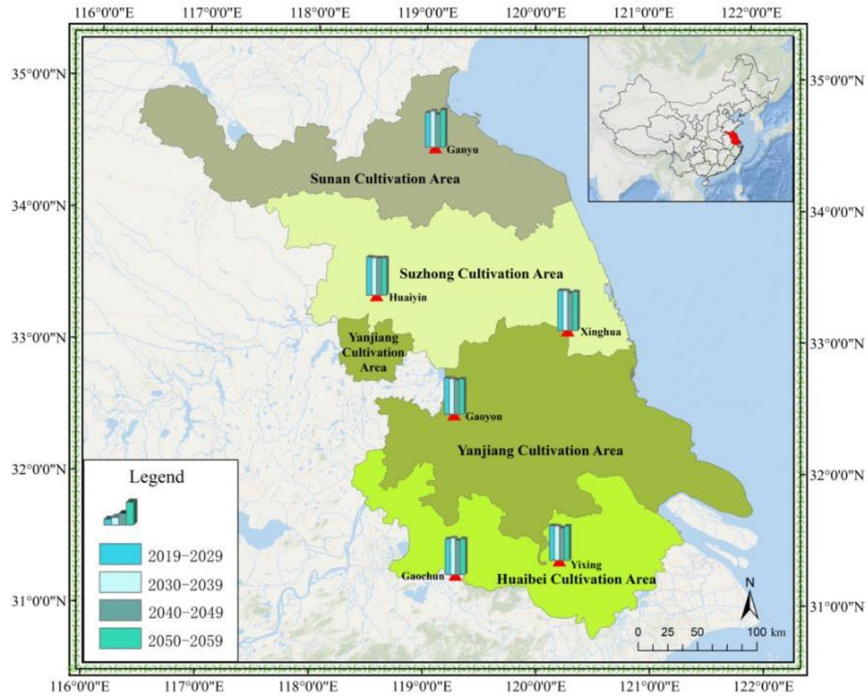

Figure 8: Average rice yield of each site in the Jiangsu province.

Table 9: The average yield per unit area of the six sites.

Site	Huaiyin Site	Ganyu Site	Gaochun Site	Xinghua Site	Yixing Site	Gaoyou Site	Average
Yield per unit area (kg/ha)	7912.70	7460.88	7512.29	8212.76	7167.00	7440.98	7617.77

As shown in Fig. **9**, the fluctuations in the yield per unit area at each site during 2019–2060 were generally consistent, showing a downward to stable trend. The dispersion of yield per unit area at each site was as follows: Gaochun > Xinghua > Ganyu > Yixing > Huaiyin > Gaoyou, indicating that Gaochun had the most stable yield per unit area, followed by Xinghua, Ganyu, and Yixing. Huaiyin and Gaoyou had the greatest fluctuation, with the most unstable yield per unit area.

4. Discussion

4.1. Response Analysis of Rice Yield and Meteorological Factors

Drawing upon the rice yield data, climate data, correlation analysis, and multiple linear regression model, we explored the response relationship of rice yield to climate and its regional differences. By analyzing the correlation between single factor (precipitation, temperature, and solar radiation) and rice yield at each site and using the multiple linear regression analysis between the average annual meteorological factor values and the average annual yield in the Jiangsu province, we identified the impact of meteorological factors on the yield at each site and the total yield of Jiangsu province.

(1) On the one hand, excessive precipitation will reduce the oxygen content in rice fields, leading to a decrease in the rice tillers number and the inhabitation of rice growth and development [31]. On the other hand, during the critical growth stages, such as the heading-flowering stage, excessive precipitation will cause potential flood and

rainstorm disasters, which are unfavorable to rice flowering and pollination, and ultimately affect the total rice yield [32].

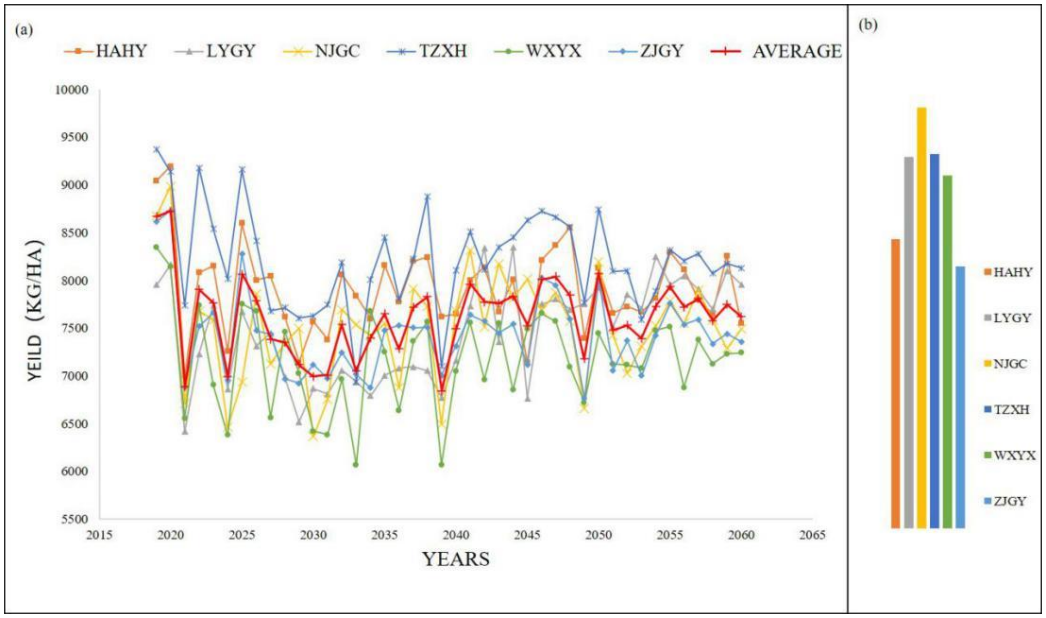

Figure 9: (a) Broken line chart of predicted yield at each site in the Jiangsu province from 2019 to 2060 (b) Dispersion of simulated value (HAHY: Huaiyin site; LYGY: Ganyu site; NJGC: Gaochun site; TZXH: Xinghua site; WXYX: Yixing site; ZJGY: Gaoyou site).

(2) The results showed that 28-32 ℃ was the optimum temperature for the germination of rice seedlings. The optimal temperature for tillering, panicle differentiation, and heading was approximately 20 ℃, 30 ℃, and 25-35 ℃, respectively. In terms of flowering, the optimal temperature was approximately 30 ℃. Temperatures lower than 20 ℃ or higher than 40 ℃ were not conducive to fertilization [33]. Statistical data analysis showed that the rice yield would decrease by 14 % for every 10 ℃ daily temperature increase [34]. Therefore, the proper temperature rise is favorable to increase rice yield; however, a high temperature will have a significant negative impact on rice yield. This is because high temperatures will accelerate rice growth and development and reduce the number of rice tillers. Thus, the total dry weight and panicle weight will be reduced [35]. In addition, heat damage caused by high temperatures will reduce the seed setting rate of rice, leading to yield reduction. Additionally, high temperature also promotes weed and pest infestation.

(3) The increase in sunshine hours in the rice-tillering stage was beneficial to the increase of rice yield per unit area. The increase in sunshine hours and the temperature difference between day and night during the rice flowering and fruiting stage may potentially increase the rice yield per unit area [36]. Moreover, rice is also very sensitive to water demand. In the jointing-heading stage, an increase in solar radiation aggravates the rice leaf evaporation, leading to insufficient water supply and affecting the formation of rice grains. This also explained the negative correlation response of rice yield to solar radiation at certain sites.

In the context of global warming, climate change has increased the amount of heat received by the Jiangsu province in the rice-producing areas. Our results can help the relevant departments strengthen early warning of meteorology and information release, take remedial measures in time and take active measures to pursue advantages and avoid disadvantages [37].

The limitations of our study are: (1) Linear correlation and multiple regression analysis models have limitations when used to analyze the impact of meteorological factors on rice yield. It is necessary to explore a response model more in line with the complex action mechanism of meteorological factors, which is closely related to the regional characteristics of agricultural production. (2) Our study does not highlight the impact of meteorological disasters on rice production in the event of extreme weather. Therefore, future studies should use the extreme weather scenario data to explore the effect of extreme disaster weather on rice production and observe the impact of climate change on rice production. (3) Our study focused on the influence of meteorological factors on rice yield throughout the whole rice growth cycle. However, more detailed and subdivided research is required to identify the impact of meteorological factors on rice yield during each growth stage. It is necessary to refine the time points of rice vegetative growth and reproductive growth and carry out phased data analysis to obtain a more accurate analysis.

4.2. Rice Yield Prediction Based on the DSSAT Model

We used the DSSAT crop growth model to simulate the rice yield per unit area over the years. Comparing the simulated values by the model and observed values of rice, including flowering stage, maturity stage and yield, indicates a strong positive correlation and consistency between the simulation results and the observed values. The calibrated rice variety parameters can reflect the main genetic characteristics of rice varieties accurately. Additionally, this indicate that the model has a strong simulation ability for rice growth and development and yield, which can be used for the research of crop production potential simulation. Considering the influence of abnormal factors, such as diseases, pests, and extreme weather, some errors are bound to exist between the simulated and actual measured values. The results indicated that the errors were within a reasonable range. The calibrated and adjusted rice genetic parameters can fit the rice varieties of each site. Hence, the model can perform a good simulation on the rice yield in the future by using the calibrated parameters. Governments at all levels can implement corresponding policies using the simulated and predicted fluctuation in the yield per unit area at each site. Additionally, relevant departments can strengthen the guidance of agricultural production and make reasonable plans regarding grain purchase, sales, and transportation, which has important theoretical and practical significance for maintaining the stability of rice yield and grain production in the Jiangsu province.

Notably, the soil conditions and field management status were assumed to remain unchanged for a period of time. Our results can reflect the impact of climate change on the rice yield per unit area and support relevant departments and farmers to take reasonable field management measures while accounting for climate change.

The limitations are: (1) The data of rice irrigation at each site adopted the irrigation water quota value of various regions in the Jiangsu province, and the impact of diseases and pests were excluded. (2) Because rice growth and its influencing factors are complicated, can be affected by many internal and external factors, and the model simulation was a multi-system interaction process, it was difficult to involve various changeable actual situations comprehensively. For example, when the DSSAT model simulated the yield, it was unreasonable to assume that the canopy structure of rice was uniform. The representativeness of localized varieties is not high enough, which needs to be further verified by different rice varieties. (3) The uncertainty of climate change forecast will lead to a certain deviation in rice yield prediction. Thus, many extremely special natural conditions can be involved in yield estimation to improve the accuracy of model simulation. (4) The DSSAT model was effective in estimating the rice yield, based on a single point scale. However, if the site-based one-dimensional model is extended to a two-dimensional regional scale, it will be difficult for the DSSAT model to process regional-scale crop parameters, field management, and other information. Therefore, future studies need to improve the model and combine the model with GIS, remote sensing, and other technologies to focus on how to deal with spatial variation and carry out adaptive verification to make the simulation results applicable to more dimensions.

5. Conclusion

Under the research framework of rice yield and climate change response analysis, we used the DSSAT crop yield estimation model to simulate the changes in rice yield of typical sites in Jiangsu province, China. In addition, we explored the spatiotemporal characteristics of rice yield in the Jiangsu province while considering climate change and identified the response relationship between rice yield and changes in the meteorological factors. To provide a basis for formulating policies to maintain the stability of rice yield in the Jiangsu province, the following conclusions were obtained:

(1) In this study, the DSSAT crop growth model was used to simulate the annual rice yield per unit area at six typical rice planting sites in four rice-cropping areas of Jiangsu province from 1990 to 2018. By comparing the

simulated values by the model and the observed values of rice parameters such as flowering, maturity and yield, this study found that the values of NRMSE between the simulated and measured values after parameter calibration are all less than 10%, the values of d are all close to 1, the simulated value of yield is in good agreement with the measured value. Considering the influence of aberrant factors, such as diseases, pests and extreme weather, there must be some errors between the simulated and observed values. However, our study indicated that the errors were within a reasonable range. Hence, the calibrated rice genetic parameters can fit the rice varieties at each site effectively and the model can carry out a good simulation on the rice yield in the Jiangsu province under the influence of climate change.

(2) In this study, we employed the method of control variables. The meteorological data of RCP4.5 medium and low GHG emissions and radiation forcing scenarios derived from the CMIP5 climate prediction downscaled dataset were used to predict the changes in the yield per unit area at six typical rice sites in the Jiangsu province under 41 long-term time series. The results showed that the yield per unit area at each site fluctuated (within a certain range) with time. Xinghua had the highest average yield per unit area, and Gaochun had the most stable fluctuation of yield per unit area. Overall, the yield per unit area of rice showed a downward trend, tending to be stable gradually.

(3) Our results showed that precipitation, temperature, and solar radiation had a certain linear correlation with rice yield. The linear correlation had regional differences. An increase in precipitation was conducive to the increase of rice yield at all sites in the Jiangsu province. An increase in temperature affected the total rice yield in the Jiangsu province negatively, but it had a positive impact on the yield in HAHY. The increase in solar radiation value, i.e., sunshine duration, exerted a negative impact on the rice yield of sites located in the north and west of Jiangsu province; however, it had a positive effect on the rice yield of sites located in the south and east of the province. With respect to the total rice yield in the Jiangsu province, the increase in solar radiation had a promoting effect.

To cope with the adverse impact of climate change on rice production in the Jiangsu province and enhance the comprehensive production capacity of rice, it is possible to formulate regionally differentiated countermeasures that are based on local conditions; these include promoting double-cropping rice, cultivating new varieties and advanced technology, rationally adjusting rice distribution, strengthening the construction of farmland water conservancy facilities, promoting effective water and fertilizer management practices, and adjusting the sowing date in line with the meteorological forecast.

Acknowledgment

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