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Research Article

Characters Meteorological Yield Dynamic Prediction of Spring Maize Using Climatic Suitability Model

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Abstract

Crop yield prediction is an essential component in agricultural management decisions. The meteorological yield could more accurately evaluate the weather impact without agricultural technology progress. The meteorological yield of spring maize was assessed by an Integrated Climatic Suitability (ICS) model with a daily climate factor, such as temperature, moisture, sunshine, and precipitation, in the Liaoning province of China. The result showed that the and predicted yield of spring maize was significantly correlated among maturity types (R^2=0.46-0.52, P<0.01) and among different regions (R^2=0.34-0.68, P<0.01). The yield of most years was accurately forecast with the Relative Standard Errors (RE) < 5%, which mainly resulted from the differences of daily average climatic suitability (F) and cumulative climate suitability index (B_{jk}) among regions, chronologies, and coordination diversity. Thus, the ICS model is suitable for forecasting the meteorological yield of spring maize for arranging farming activities in this region.

Keywords: Agricultural management decision; Climatic suitability model; Forecast; Physiological growth period; Spring maize; Yield

Introduction

Climate change is becoming a very important aspect of agriculture problem for the world population [1,2]. It is globally recognized by scientists and the governments. China's climate has also undergone a significant change resulting in significant impact on agricultural production of the country [3,4]. Agricultural producers, researchers, consultants, and industry representatives are faced with crop management and decisions throughout the growing season [5]. If this crop is in threat that means food supply will be affected. It plays a vital role of the grain output forecast in the entire government regulation. Grain yield forecasting technology has always been an important research topic.

It is the popular research about the impact of climate change on agricultural output in the world. However, it has always been difficult to accurately forecast the yield [6]. In recent years, many scholars have studied the relationship between climate resources and ecological adaptability of the crop [7,8]. And they have made certain progress in crop climate suitability index assessment, crop yield forecasting, agro-ecological zoning, etc [9-12]. Crop modeling is important to enhance the understanding of plants because they are complex and dynamic [13]. Previous studies are mostly based on the whole growth period [14,15]. Their methods of crop yield predicting are static analysis and paid little attention to the response regular pattern to the light, temperature and water.

Liaoning Province is located in the south of the northeast region of China. Various agro-meteorological disasters occur frequently causing by global warming, which exacerbates the uncertainty of agricultural production. Spring maize is the primary grain crop in Liaoning Province, and its planting area accounted for 2.18×10^4 hm^2 about 6% of China in 2017 [16]. The analysis of the influence of meteorological conditions on spring maize production has always been one of the essential meteorological services. With the development of agricultural meteorological modernization business, traditional qualitative evaluation could no longer meet the needs of business work.

In this study, we collected historical data of meteorological elements and historical data of 9 physiological development stages of spring maize by an improved ICS model with a daily climate factors to calculate and study the influence of meteorological conditions on the growth of maize in different growth periods in Liaoning Province, China. And then we dynamically predicted maize yield with a daily time step by an yield model based on meteorological Yield (Y_w).

Materials and Methods

Study area

Liaoning Province is located in northeastern China (118°50'E -125°47'E, 38°43'N -43°29'N) with the area of 14.8×104km2. The region is characterized by a temperate continental climate with an average annual temperature of 5.2-10.9°C, annual precipitation of 445-1067mm and a frost-free period of 131-223 d [17]. The spring maize planted in the region exceeded 2.0×104km2 since 2016. Typically, spring maize is planted in spring (mid to late April-early May) and harvested in autumn (October), with only one planting season per year [18].

Data collection

The 13 meteorological stations were located at Haicheng, Wafangdian, Benxixian, Chaoyangxian, Suizhong, Xinmin, Xiuyan, Zhuanghe, Kuandian, Fuxinxian, Zhangwu, Jianchang and Changtu in Liaoning Province (Figure 1). The average daily air temperature, total precipitation, sunshine hours, and soil moisture from 1981

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to 2010 were obtained from China's National Meteorological Information Center of China.

Daily climate suitability index

An integrated comprehensive climate suitability model was An integrated comprehensive climate suitability model was established by considering Temperature (T), Precipitation (P), Sunshine (S), and Soil Moisture (W) at each growth stages of spring maize as follows:

$$F(C)_i = aF(T)_i + bF(P)_i + cF(S)_i + dF(W)_i \quad (1)$$

Where $F(C)_i$ is the daily climate suitability index for the day i of each growth period of spring maize (The growth period of spring maize was divided into 9 stages: Sowing to germination (SOW), Germination to trefoil (GER), Trefoil to 7 leaves (TRE), 7 Leaves to jointing (7LE), Jointing to tasseling (JOI), Tasseling to flowering (TAS), Flowering to silking (FLO), Silking to milk (SIL), Milk to maturation (MIL)); *a*, *b*, *c*, and *d* are weight coefficients [19].

Cumulative climate suitability index

Based on the daily climate suitability index (Equation 1), cumulative climate suitability index (B_{jk}) of spring maize was calculated at each physiological growth period. The cumulative climate suitability index was regarded as the indicator of the physiological growth of spring maize. The B_{jk} at each stage are as follows [20]:

$$B_{jk} = \sum_{i=1}^{m} F(C)_i \quad (2)$$

Where B_{jk} is cumulative climate suitability index at k stage in j year; m is the duration of each physiological growth stage (days); i is the day from 1 to m in the k stage (days).

Meteorological yield forecasting

The yield of maize is divided into the trend yield and the meteorological yield. The trend yield is characterization affected by social factors such as agricultural technology, which usually shows that the yield increases continuously with time. The meteorological yield affected by climatic changes may be positive or negative. Thus, the yield of spring maize is expressed in the Liaoning Province as,

$$Y = Y_i + Y_w \quad (3)$$

Where Y is yield (g/m^2); Y_i is the trend yield; Y_w is the meteorological yield. This article uses the yield before 5 years as the trend yield.

Y_w was established by the average daily *F(C)* with corresponding weight coefficient at each growth period as follows:

$$Y_w = a + X_1F_1 + X_2F_2 + X_3F_3 + X_4F_4 + X_5F_5 + X_6F_6 + X_7F_7 + X_8F_8 + X_9F_9 \quad (4)$$

Y_w is the meteorological yield; X is weight coefficient. 1: SOW; 2: GER; 3: TRE; 4: 7LE; 5: JOI; 6: TAS; 7: FLO; 8: SIL; 9: MIL. a is a constant;

Model testing

The Relative Errors (*RE*) was used to analyze the consistency and accuracy between the predicted yield and the investigated yield as follows:

$$RE(\%) = (P - M) \times 100 / M \quad (5)$$

Where *P* is the predicted value, *M* is the investigated value.

Data analysis

The climate factors and maize growth period were analyzed with C# software for the subordinate climate suitability models. Based on the meteorological variables and the yield of spring maize, the weight coefficients for Temperature (T), Precipitation (P), Sunshine (S), Soil Moisture (W) were determined in IBM SPSS Statistics 20 (SPSS Inc, Chicago, IL, USA). The prediction of the meteorological yield and yield of spring maize was carried out using R 2.11.1. Figures were drawn using SigmaPlot 14.0 and ArcGIS 10.2.2 software.

Results

Investigated and predicted yield of spring maize among maturity types

The investigated and predicted yield of spring maize among maturity types were compared in 1986-2010 (Figure 2). A linear relationship between the predicted and observed values were found

Figure 1: Sampling sites in liaoning province.

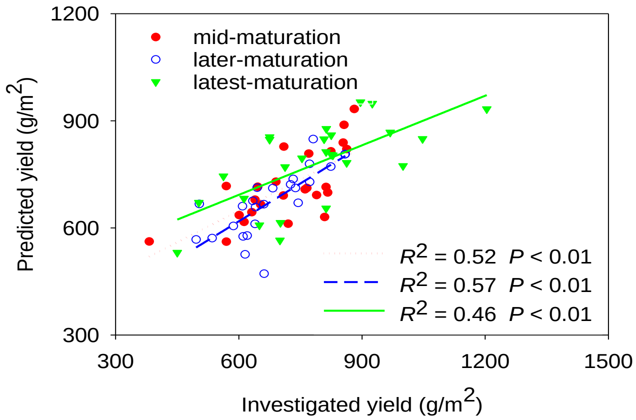

Figure 2: Correlation between the investigated and predicted yield of spring maize among maturity types in 1986-2010.

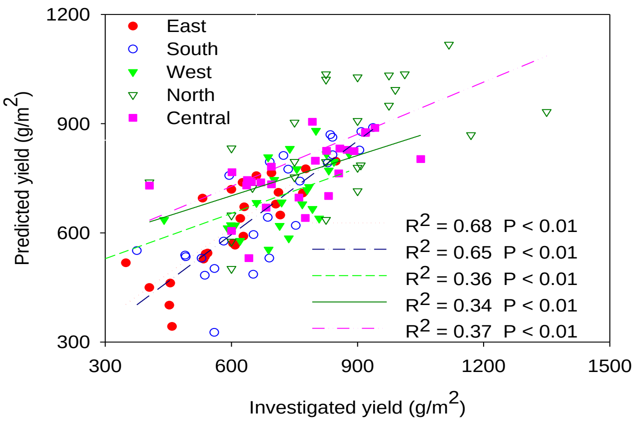

Figure 3: Correlation between the investigated and predicted yield of spring maize among different regions of Liaoning Province in 1986-2010. (East: Benxixian, Kuandian; South: Wafangdian, Zhuanghe; West: Chaoyangxian, Zhangwu, Fuxin, Jianchang, Suizhong; North: Changtu; Central: Xinmin, Haicheng, Xiuyan).

with the correlation coefficient (R^2) of 0.46-0.52 with P<0.01. The R^2 was relatively low with the latest-maturation type, while the highest with the later-maturation.

Investigated and predicted yield of spring maize among different regions

The investigated and predicted yield of spring maize among different regions were compared in 1986-2010. The correlation coefficient (R^2) of different areas was 0.34-0.68 with P<0.01(Figure 3). A linear relationship in the southeast between the predicted and observed values was higher with the correlation coefficient (R^2) of 0.34-0.36 than the ones in the northwest with the correlation coefficient (R^2) of 0.65-0.68.

Relative error between the predicted and measured yield

The yield of spring maize was predicted using the ICS model of different maturity types spring maize in 1986-2010 (Figure 4). The Relative Errors (RE) between the predicted and measured values were mainly concentrated in the range of less than 5% from 1986 to 2010. It reached 64%. The forecast yield of most years was accurate, but there were also rare cases where the RE was greater than 20% due to

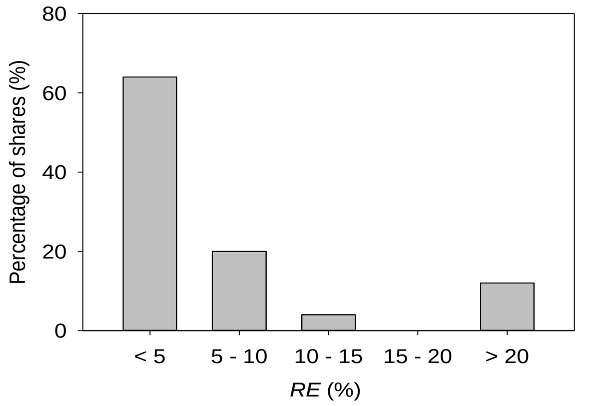

Figure 4: Relative Error between predicted and investigated yield in 1986-2010. (Percentage of shares: the probability of Relative Error).

extreme weather conditions in some years (12%).

Regional error analysis

By comparing the distribution maps between climatic suitability and meteorological yield (Figure 5), there was a consistency of changes in the meridional distribution. Their contours showed a band distribution characteristic of high → low → high → low. Their synchronicity in zonality was not obvious. It indicated that there was a certain error about measuring meteorological yield in different regions from east to west by means of the climate suitability index.

Chronological error analysis

With the development of the times, it gradually develops from high climate suitability index , high climate yield or low climate suitability index and low climate yield to the opposite direction (Figure 6). The positive correlation between them gradually weakened. Its development process gradually incorporates factors other than climate conditions impacting on yields.

Error analysis of Coordination diversity between daily average climatic suitability and cumulative suitability index

It could be seen from the results of the relationship among daily average climatic suitability, cumulative climate suitability index and meteorological yield that meteorological yield as increased with a good coordination of daily average climatic suitability and cumulative climatic suitability, and the other with the climate conditions with higher climate suitability index or higher cumulative climatic suitability (Figure 7). When the climatic suitability was 0.610 and the cumulative climatic suitability reached 90, there was a peak in meteorological yield. Therefore, if the meteorological conditions were nicer in the year, and what's more, the maize growth period was longer, then the meteorological yield would be higher. If the meteorological conditions were particularly good or not, the growth period of maize could be shortened, which in turn led to a low cumulative climatic suitability and a decline in meteorological yield. If the meteorological conditions were not good enough to meet the normal growth needs of maize, the climatic suitability dropped. And then the growth of the maize slowed down. Its growth periods were prolonged. In that condition even if the cumulative climatic suitability was slightly higher, the meteorological yield could not be improved. In addition,

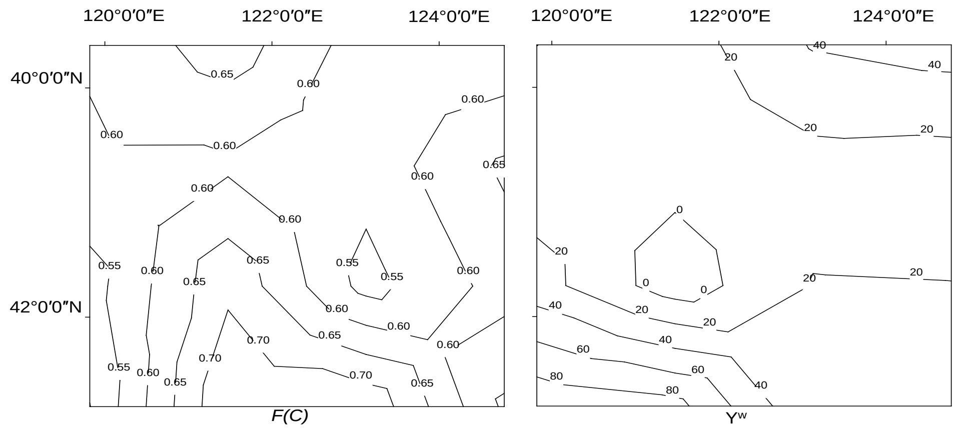

Figure 5: Spatial distribution of meteorological yield and climatic suitability yield.

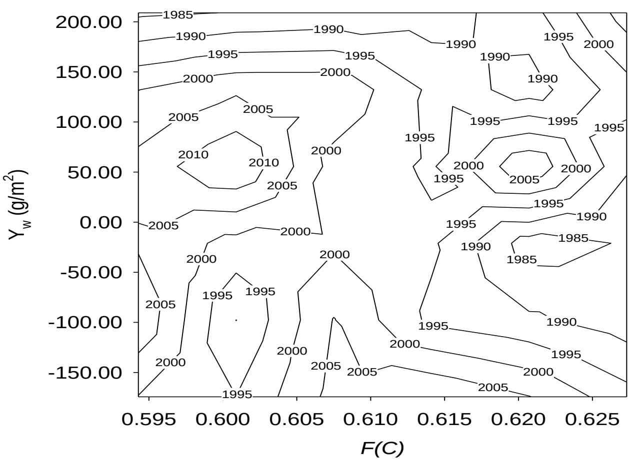

Figure 6: Spatial distribution of meteorological yield and climatic suitability yield.

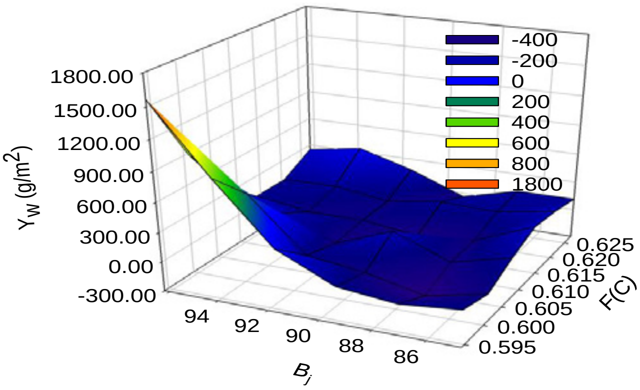

Figure 7: Meteorological Yield (Y_w) related with the daily average climatic suitability index (*F(C)*), cumulative climatic suitability index (E_j).

when the climatic suitability was extremely low, if the cumulative climatic suitability could be still enough and remained high, high climatic yields could be unexpectedly got, in theory. However, this situation was not the actual measured data in this paper. So it does not exist. In actual production, it is hard to achieve.

Therefore, the same as the climatic suitability, cumulative climatic suitability is an important indicator of meteorological yield. If the yield of maize is needed to forecast in the early stage of growth during a growing season, the days from sowing to maturing for the maize were unknown, it was difficult to predict the cumulative climate suitability index. For that, a way to predict the length of the growing season must be found. The climatic suitability and cumulative climatic suitability were made to predict meteorological yield. The errors in forecasting climate output could be reduced to a great extent.

Discussion

Dynamic forecast model in the yield model

In recent years, many scholars have carried out a lot of research based on climate suitability theory [21-23]. It continuously develop and improve the climate suitability theory to measure the impact of various meteorological elements on crop growth, which is conducted and applicated in crop growth evaluation, growth period simulation, yield prediction, etc [14,24,25]. At present, it is always based on the yield forecasting models to analysis and forecast the crop yield every ten-days or a month, which undoubtedly weakens the differences in response of specific crops to different meteorological conditions during different growth periods [26]. The growth of crops is a continuous and dynamic process. It also changes continuously to the needs of crop for environmental conditions. Thus, the ICS model can be applied to forecast the yield for the growth period at the whole and most physiological stage of spring maize in Liaoning Province for the agrometeorological service. This method of predicting crop yields every one day will make forecasting results more accurate.

Phase characteristics of climate change

As we all know, climate change is a quasi-periodic process with obvious characteristics of phase changes. The shorter process is short as a weather process (5-7 days) or weather stage (20-330 days). And the longer one is just like a climate phase (5-20 years) or Historical climate period (cold or warm). The characteristics of gradual climatic changes would be bound to cause the crop yield alteration. It has obvious gradual changes too. When the crop yield model forecast in this paper is applied in business, the parameters of the yield model and ICS model should be adjusted according to the characteristics of the climate change at that time. If then, the forecast results would be more accurate.

Human wishes constantly change model parameters unawarely

Human activities are projected to lead to substantial increases in temperature. Therefore increases in yield and expansion of climatically suitable areas are expected to dominate in some districts [27-29], whereas disadvantages from increases in water shortage and extreme weather events (heat, drought, storms) will dominate in the other areas [30-32]. The adaptation options that may be explored to minimize the negative impacts of climate changes and to take advantage of positive impacts. Humans will take a variety of means such as changing in crop species, cultivar, sowing date, fertilization, irrigation, drainage and farming system seem to be the most appropriate [33]. These methods adopted by humans will undoubtedly cause great uncertainty to the output forecasting model. This article used climate yield instead of pure yield to measure, which minimized the crop yield errors due to technological development. Consequently the impact of meteorological conditions were attributed to the crop climate yield.

Regional characteristics and local microclimate change

Climate change always differently affect agricultural microclimate changes in various districts [34]. In order to make the evaluation of the impact of meteorological factors on the growth of corn more objective and comprehensive, we researched the growth and development of spring maize from its physiological needs. Also the changes of soil moisture caused by precipitation to the runoff, the precipitation infiltration, the delay of the impact of precipitation and soil texture in different regions variations was considered. The ICS model combinating of rainfall suitability and soil moisture suitability functions was used to construct the climate suitability index, which made the evaluation and forecast of spring maize growth more realistic, and improved the forecast accuracy. The effect of extreme meteorological conditions, such as hail, wind, and heavy rain, on maize growth, is not elucidated in this study. Therefore, further researches should focus on the effect of the meteorological disaster on the growth period prediction in the ICS model. In addition, this model needed to decrease the error of yield simulation due to factors such as local planting density, nutrient balance (nitrogen, phosphorus, potassium, etc.), diseases, insects, and grass damage.

Conclusion

The ICS model was constructed by setting individual weight coefficients and newly added subordinate function of soil moisture by using 30 years of agricultural meteorological observation data from 1982 to 2010 in Liaoning Province of northeast China. The yield of spring maize was predicted by the yield model and the ICS model on a daily basis by the characteristic of each physiological stage. The weighting coefficient of climatic suitability for each growing stage of maize was calculated separately. The parameters of the subordinate function of temperature, precipitation, sunshine, and soil moisture were further adjusted according to the actual data at each physiological growth period of spring maize. The accuracy of the model was fully satisfied with the need in the agrometeorological forecast. Therefore, the yield model can be applied to forecast the yield of spring maize automatically correct daily in the Liaoning Province of northeast China. And what's more, the emerging error was analysis including zonal discrepancy, chronological difference, and coordination diversity between daily average climatic suitability and cumulative climate suitability index during the growing season. That was objectively evaluated the cause of the model error, which provided a theoretical basis for the subjective judgment to revise the yield result in actual work.

Acknowledgement

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