The Relationships Between Extreme Precipitation and Rice and Maize Yields Using Machine Learning in Sichuan Province, China

Jun Fan[1]*, Attachai Jintrawet[2] and Chanchai Sangchyoswat[2]

[1]Agricultural System Resource Management Program, Center for Agricultural Resources System Research, Chiang Mai University, Chiang Mai, Thailand
[2]Department of Plant and Soil Sciences and Center for Agricultural Resource System Research, Chiang Mai University, Chiang Mai, Thailand

Received: 26 February 2020, Revised: 20 May 2020, Accepted: 10 June 2020

Abstract

Rice and maize are two staple crops that play a critical role in food security in the southwest of China. They are sensitive to extreme climate events such as drought and flood. Therefore, the assessment of the future production of these crops in an era of climate change is essential. However, current assessment tools are time consuming and require extensive input datasets and expert knowledge. This study is an attempt to provide an alternative tool for prefecture level users using an aggregate Z-index which uses precipitation as an input. A machine learning algorithm (Random Forest) was introduced to build and train the model. Finally, future precipitation projected from Global Climate Models (GCMs) was used as an input to assess the future rice and maize yield variations. This tool outperformed other conventional statistical tools and was especially suitable for assessing extreme cases. Crop yields are significantly affected by drought in the study area. Z-indexes derived from three GCMs on decadal time scales were used for assessing future yield variations. Under the lower emission Representative Concentration Pathway (RCP) 4.5, average maize yields and rice yields are likely to be reduced by -0.58% and -1.49%, respectively, over the next three decades in Mianyang prefecture compared to the baseline period. Similarly, under the higher emission (RCP) 8.5, maize yields and rice yields may decrease by -0.75% and -1.30%, respectively. This assessment tool can be applied in other locations, providing that datasets are available to meet the user's needs.

Keywords: extreme precipitation, machine learning, climate scenarios, yield forecasting, random forest
DOI 10.14456/cast.2020.30

*Corresponding author: Tel: 053-221275, Fax: 053-210000
Email: thebestone2007@sina.com

1. Introduction

Rice and maize are the dominant crops in Sichuan province, accounting for about 90% of the total cereal grain output and about 83% of the food crop sown in the area in 2017 [1]. Rice is fully irrigated, while maize is mostly rainfed in this area. Rice is the staple food for human consumption and maize is the major animal feedstuff. Thus, the production of rice and maize is critical for food security and the national self-sufficiency policy [2-4]. However, rice and maize production is sensitive to extreme climate events. For example, the big droughts in 1994 and 2006 severely damaged crop production [5, 6].

Extreme climate events are projected to be more frequent and intensive in the future due to climate change [7]. Although extreme climate events are defined by different criteria and thresholds, abnormal temperature and extreme precipitation are the main extreme climate events and are widely studied [8, 9]. In the southwest part of China, droughts and floods, which are related to extreme precipitation, are key extreme climate events [10, 11]. Extreme climate events inevitably affect an ecosystem's quality and productivity. Chen *et al.* [12] found that extreme climate events have decreased Gross Primary Productivity by 2.8% annually in China over the past three decades. They also highlighted that Gross Primary Productivity is more sensitive to drought than to other factors. Moreover, that extreme climate events directly damage crop yields has been reported by many researchers using different methods such as crop models and econometrics [13-17]. Drought, heat and heavy rain are the three main extreme events that affect crop production [18].

The effects of extreme climate events on agricultural systems are expected to increase in the future [19]. Therefore, anticipating and assessing the influence of extreme climate events on crop yield is important for better decision making. When studying the effects of future extreme climate events on crop yield, two crop model families, namely DSSAT (Decision Support System for Agrotechnology Transfer) and APSIM (Agricultural Production Systems Simulator) are widely used for simulating crop yield and other variables. However, these crop models do not fully capture the impact of extreme events [18]. Moreover, the use of crop models often requires expert knowledge and an extensive number of input datasets, which are lacking at the prefecture level [20]. The aim of this study is to provide a reliable alternative assessment tool that captures the impact of key extreme climate events (extreme precipitation) on rice and maize production. Consequently, the decision makers at prefecture level can apply the tool to gain better understanding of the relationships between crop production and extreme precipitation and adjust their policies accordingly.

2. Materials and Methods

2.1 Study areas

Mianyang, Dazhou and Leshan prefecture-level cities in Sichuan province, China (Figure 1) were chosen to be the study areas as they are typical crop production areas distributed in the eastern Sichuan province (the western Sichuan province is one part of the Tibet Plateau and has a different agricultural system). Mianyang was chosen to be the main study area, while Dazhou and Leshan were used to validate the assessment method. The climate zone of the study areas was warm temperate, winter dry and hot summer. Historic annual precipitation for Mianyang, Dazhou and Leshan are 546-1237 mm, 874-1693 mm, 769-1720 mm, respectively [1]. The main crops in the study areas are rice, maize and wheat.

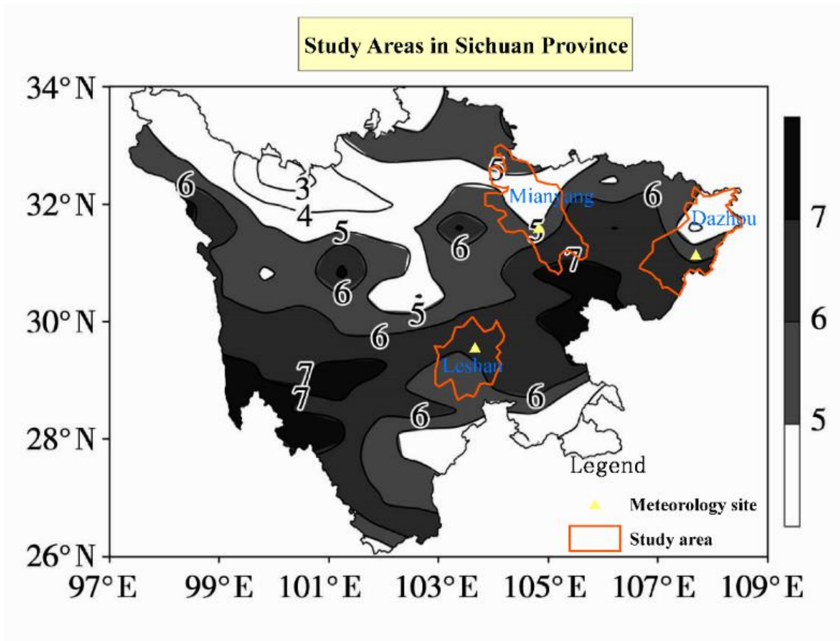

Figure 1. Location of the study areas (red polygon) in Sichuan province. The background map is the drought map in 2006 summer based on Z-index [23], the darker and the higher number is the drier zone

2.2 Defining extreme precipitation by the aggregate Z-index

This study focused on precipitation-related extreme events because the frequency of temperature-related extreme events such as maximum temperatures showed little change in the study area, and the intensity of heat waves was even decreasing. On the other hand, precipitation-related events such as droughts were increasing in terms of frequency [21, 22]. The Palmer Z-index is a method to calculate short-term drought, and it was applied in Sichuan province, China [23]. Assuming monthly precipitation follows a generalized gamma distribution, it can be transformed to normal distributions [23]. The transformation process is as follows:

$$Z_i = \frac{6}{C_s}\left(\frac{C_s}{2}\varphi_i + 1\right)^{\frac{1}{3}} - \frac{6}{C_s} + \frac{C_s}{6} \tag{1}$$

$$C_s = \frac{\sum_{i=1}^{n}(X-\bar{X})^3}{n\sigma^3} \tag{2}$$

$$\varphi_i = \frac{X-\bar{X}}{\sigma} \tag{3}$$

Where Z_i is the index value, C_s is a coefficient, φ_i is the normalized precipitation variable, X is the monthly precipitation amount, n is the number of total samples, and $\bar{X}$ and σ are the mean and standard deviation of X respectively.

After calculating the Z-index, the extreme events can be classified into seven categories by distribution quantiles. These seven categories are ‘Extreme dry’, ‘Severe dry’, ‘Moderate dry’, ‘Normal’, ‘Moderate wet’, ‘Severe wet’ and ‘Extreme wet’. Table 1 lists the details of all the seven categories.

Table 1. The categories of extreme events based on monthly precipitation and its Z-index values

Category	Value Range	Quantile
Extreme dry	Z<-1.65	less than 5%
Severe dry	-1.65<Z<-1.04	5%--15%
Moderate dry	-1.04<Z<-0.52	15%--30
Normal	-0.52<Z<0.52	30---70%
Moderate wet	0.52<Z<1.04	70%--85%
Severe wet	1.04<Z<1.65	85%--95%
Extreme wet	Z>1.65	greater than 95%

Using precipitation data, we first calculated the monthly Z-index during the crop growing period, which is from April to August in the region. Next, except for the Z-index values which fell into the normal category, all remaining negative Z-index values were aggregated into a drought class, and all remaining positive Z-index values into a flood class. For example, the Z-index values for April to August 1987 were 0.36, -1.02, 1.9, 0.66, -0.09, so the aggregated wet value which denoted flood was 1.9 + 0.66 = 2.56. We did not add 0.36 into the aggregate wet value as it fell into the Normal category. Likewise, the aggregate dry value was -1.02, as -0.09 was in the Normal class.

2.3 Historic and future precipitation data

Historic daily precipitation data for the three study areas from the years 1985 to 2017 were obtained and cross-checked from the China Academic of Agricultural Engineering's greenhouse data program (http://data.sheshiyuanyi.com/WeatherData/), Statistical Bureau of Sichuan (http://tjj.sc. gov.cn/tjcbw/tjnj) and the Statistical Bureau of Mianyang (http://tjj.my.gov.cn/myoldfiles/mytjnj/index.html). Daily precipitation data was accumulated into monthly precipitation to calculate the Z-index, then monthly Z-indices were aggregated to the yearly dataset to match the crop yield dataset. A total of 180,675 historic daily precipitation records were collected in the three study areas.

Output from three Global Climate Models (GCMs), the BCC_CSM1_1_M, the CESM1_CAM5, and the IPSL_CM5A_MR models, were bias-corrected [24] to provide projected future precipitation for Mianyang prefecture for the period 2020 to 2050. The data simulated by these models were based on the Coupled Model Inter-comparison Project phase five (CMIP5), and two future scenarios were considered: RCP 4.5 and RCP 8.5. The simulated precipitation from these three GCMs were used to calculate the future Z-index separately. We defined the future periods into three decades, namely the 2020s (2020-2029), 2030s (2030-2039), and 2040s (2040-2050) to compare and check if the simulated precipitation and corresponding Z-index were consistent. All the bias-corrected daily precipitation data were obtained from the research program on Climate Change, Agriculture and Food Security (http://www.ccafs-climate.org/data_bias_correction/) and accumulated into monthly precipitation data to calculate the Z-index. Then, the monthly Z-indices were aggregated to a yearly dataset for predicting crop yield. In total, 407,340 daily precipitation records from three GCMs were collected, and it should be noted that the data from September to the following March were not used.

2.4 Predicting crop yield by Random Forest

Machine learning algorithms such as Artificial Neural Network (ANN), Support Vector Machine (SVM) and Random Forest (RF) have been introduced for predicting crop yield in recent years. Choosing the right algorithm depends on the data and research objective. ANN and SVM require a stationary dataset, carefully scaled input data, and a large training dataset [25, 26]. However, crop yield data are typically nonstationary time-series data, so the use of ANN requires data transformation. Moreover, it has been reported in the literature that RF outperformed simple ANN, SVM, Generalized Additive Models, and K-Nearest Neighbors in the predictions that involve extreme events [13, 27]. Since the extreme cases are the focus of this study, and requirements are that the model should be simple and easy to use, and that the data size is not large, the Random Forest was chosen as the main machine learning algorithm. To evaluate the Random Forest prediction, this study also applied Multiple Linear Regression (MLR) and SVM as the benchmark.

Random Forest is one of the fundamental Machine Learning algorithms. It was invented by Breiman [28], and it is an effective statistical tool for prediction. The algorithm derives from a decision-making tree that works by asking a sequence of queries about the available data until it arrives at a decision. Random Forest decision trees randomly sample training data to build each tree and randomly set features when splitting nodes. Random Forest can be used for both classification and regression. There are many open-source packages that provide the Random Forest algorithm in different programing languages. Here, we used the Python programing language version 3.7 and the Random Forest regression algorithm available in the scikit-learn package [29]. The maximum depth parameter (max_depth) was set to 10 to avoid over-fitting, and all the other parameters were set at their default values initially. For example, the number of trees in the forest (n_estimators) was '10' and the minimum number of samples required to be at a leaf node (min_samples_leaf) was '1'. These parameters were then adjusted during the training process to find the best performance. Feature Importance is a built-in function that is used for measuring the relative importance among the input features in Random Forest. Its value for a specific feature ranges from zero to one (the higher the value, the more important the feature is), while the sum of all values is one. The value is calculated by the number of samples that reached a node divided by the total number of samples. Detailed calculations can be found in Ronaghan [30] and Louppe [31].

Similarly, SVM regression was performed using the scikit-learn package with all the parameters initially set at their default values (kernel='rbf', C=1, epsilon=0.1 and so on). They were then tuned to find the best performance.

Aggregate Z-index values (both drought and flood classes) and time were used as the input features (independent variables), whereas crop yields of each year were used as the output feature (dependent variable). Time (years) was chosen to be an input variable because temporal yield increased due to technology and management improvement [32]. Alternatively, accumulated precipitation in the crop growing season and time were also used as input features to check if using the Z-index was better than using precipitation in crop yield prediction. Historic data in Mianyang prefecture was firstly used to train and generate the model. In order to validate the model, the dataset was divided into two parts randomly: one for training, the other one for testing. Empirically, the training was set to 70-80% of the total dataset. If the percentage is too high, the model can be overloaded, and thus lack prediction capability. On the other hand, if the percentage is too low, the low number of samples cannot generate a good model. Considering our dataset, we tried the proportions of 70%, 75% and 80%, and they all generated similar results. Therefore, 75% of data was used for training. Indeed, this ratio was the default value of the split function in scikit-learn. To make the result reproduceable and accountable for the extreme dry/wet years in the training part, we set the split random state to eight. This study used R^2 and Root Mean Square

Error (RMSE) as the model's performance criteria during the comparison between observed data and model predictions. After the model was generated and tested in Mianyang, we applied this method (Z-index plus Random Forest) to another two areas (Dazhou and Leshan) to check if this method was applicable in other places.

Finally, the future aggregate Z-index values of Mianyang that were derived from bias-corrected GCMs were used to predict the future yields in Mianyang prefecture. We used the average yields from 2011 to 2017 (2010s) as the baseline to analyze the yield variations of future periods, namely, the 2020s, 2030s and 2040s.

2.5 Crop yield data

Rice and maize are two economic and staple crops in the main growing season in the study areas. Each year, crop production data as well as the harvest area at prefecture level were obtained, and then crop yields were calculated. Thirty-three years (from 1985 to 2017) of rice and maize yields for Mianyang were obtained from the Statistical Bureau of Mianyang (http://tjj.my.gov.cn/myoldfiles/mytjnj/index.html), and 19 years (from 1999 to 2017) of rice yields for Dazhou and Leshan were obtained from the Statistical Bureau of Sichuan (http://tjj.sc.gov.cn/tjcbw/tjnj). For the few years of missing data for Dazhou and Leshan prefectures, provincial yield data were used to estimate prefectural-level yield, assuming that prefectural-level yield would increase/decrease by the same proportion as the provincial yield in that year. For example, the rice yield of Dazhou in 2004 was missing. However, the yield of previous year was 7.77 (ton/ha) and the provincial yield had decreased 0.3% in 2004. Therefore, the estimate for the rice yield of Dazhou in 2004 was $7.77 \times (1\text{-}0.3\%) = 7.75$. In total, there are 104 crop yield records in the three study areas, of which 66 records are in Mianyang (rice 33, maize 33), 19 records are in Dazhou (only rice), and 19 records are in Leshan (only rice).

3. Results and Discussion

3.1 Historic crop yield, precipitation, and Z-index in Mianyang

Both rice and maize yields generally increased over the past three decades. However, yields were very low in years 1994, 2001 and 2006, mainly due to the extreme dry events. Interestingly, maize yield was low in 1986, while rice yield was not affected. Figure 2A shows the yield changes of both rice and maize from 1985 to 2017 with the aggregate Z-index values. Every significant drop in yield occurred when there was a large negative aggregate Z-index [6].

Over the past three decades, the average precipitation was 592 ± 161 mm during the rice and maize growing seasons. Typically, April and May have the lowest precipitation and July and August have the highest precipitation. The historic monthly precipitation in Mianyang prefecture (Figure 2B) roughly showed that extreme dry years happened in 1994, 2000, and 2015, while extreme wet years happened in 1988, 1998, and 2017. The Aggregate Z-index values gave more accurate assessment of the extreme dry/wet events as they were designed and accounted for the abnormal precipitation. For example, the years 2006, 1994 and 2001 were the top three extreme dry years, whereas the years 1998, 2004 and 1990 were the three wettest years (Figure 2A).

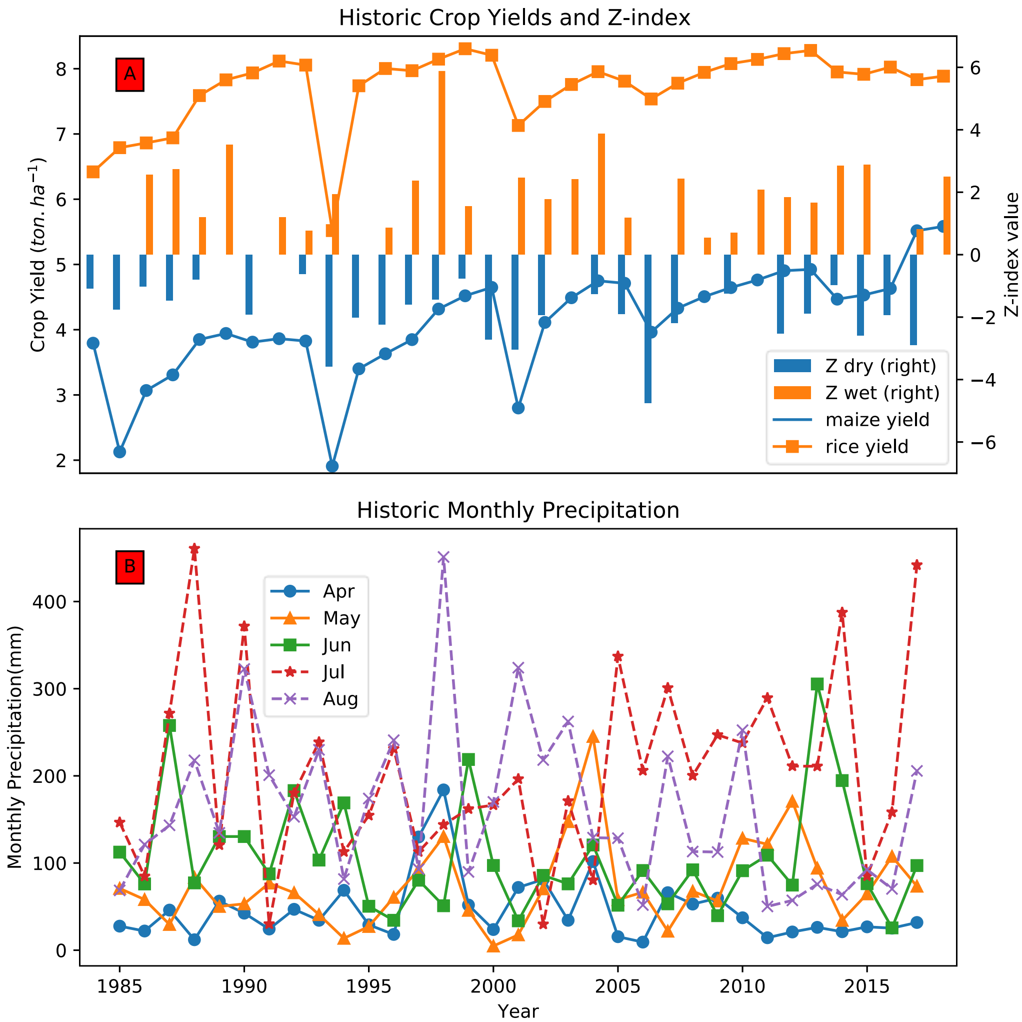

Figure 2. Historic rice and maize yields (A, left axis) and aggregate Z-index values (A, right axis) in Mianyang prefecture. The negative aggregate Z-index values represent dry events while the positive aggregate Z-index values denote wet events. B is the historic monthly precipitation from 1985 to 2017, Apr=April, May=May, Jun=June, Jul=July, Aug=August.

3.2 Performance of the models for predicting crop yield

Using the dataset in Mianyang prefecture, the various models used were trained and tested. The best parameters for the RF regression model were the default values, while the RF regression models were sensitive to the number of trees (n_estimators). For the SVM model, the kernel function parameter (kernel) was tuned to ‘linear’, the regularization parameter (C) was tuned to 0.9, and the error penalty parameter (epsilon) was adjusted to 0.47, with all the other parameters kept at the default values.

The performance of all the models is reported in Table 2. The RF+Z-index outperformed other methods, as it had the highest R^2 and the smallest RMSE for both the rice dataset and the maize dataset. The SVM models were not very different from the MLR models. Moreover, using the Z-index as input was better than using accumulated precipitation as input in the prediction. For example, the RMSE of RF+Z-index for predicting maize yield was 0.33, while the RMSE of RF+Precipitation for prediction maize yield was 0.39. RF models could capture the extreme dry years such as 1994 and 2001, which made it a favorable method to predict extreme yield variations (Figure 3).

Table 2. Performance of models, when comparing predicted crop yields to observed crop yields in Mianyang. RF represents Random Forest regression, MLR represents Multiple Linear Regression, and SVM stands for Support Vector Machine regression. RMSE means Root Mean Square Error

Method	**Maize**		**Rice**	
	R^2	RMSE (ton/ha)	R^2	RMSE (ton/ha)
RF+Z-index	0.83	0.33	0.79	0.27
MLR+Z-index	0.66	0.47	0.33	0.49
SVM+ Z-index	0.67	0.47	0.36	0.48
RF+ Precipitation	0.77	0.39	0.67	0.34
MLR+ Precipitation	0.56	0.54	0.27	0.51
SVM+ Precipitation	0.48	0.59	0.22	0.53

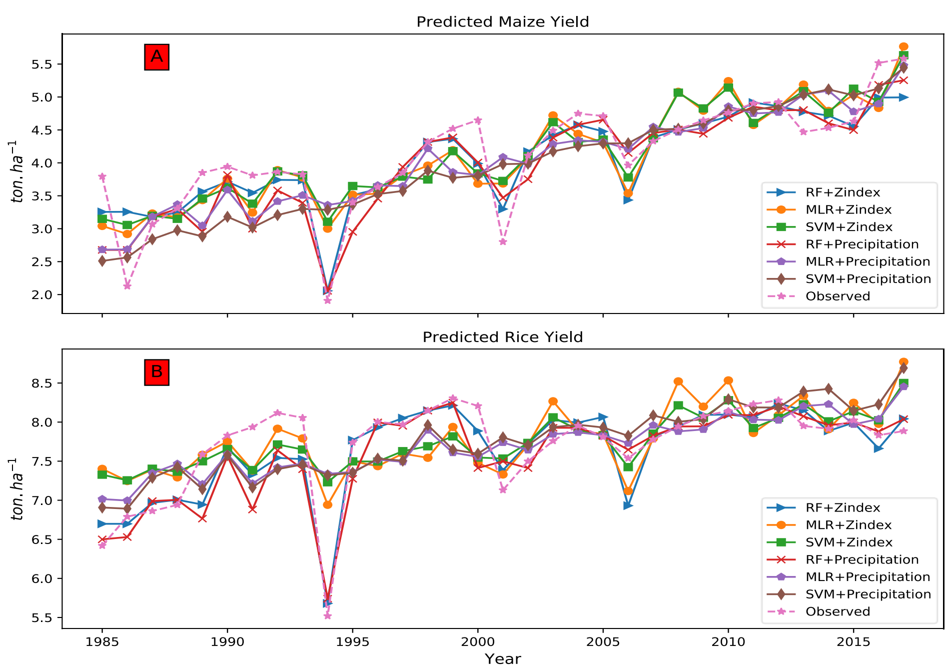

Figure 3. Predicted maize yield (A) and rice yield (B) in Mianyang by different methods. RF represents Random Forest regression, MLR represents Multiple Linear Regression, SVM represents Support Vector Machine regression. '+Zindex' means using Z-index as input, '+Precipitation' means using accumulated precipitation as input

In terms of relative feature importance for RF+Z-index models, drought could explain 38% of the maize yield change, while flood could only explain 3% of the maize yield change. Similarly, drought could explain 57% of the rice yield change while flood could only explain 6% of the rice yield change.

Since the RF+Z-index had been proven to be a favorable extreme precipitation assessment tool in Mianyang, the rice dataset in Leshan and Dazhou prefectures were used to check if the RF+Z-index was applicable in other places. After training the model, the parameter number of trees (n_estimators) was tuned to 100, and all the other parameters were kept at their default values. Figure 4 shows the predicted rice yield and the model's performance. In both places, RF+Z-index had the ability to predict rice yield with high R^2 and small RMSE values.

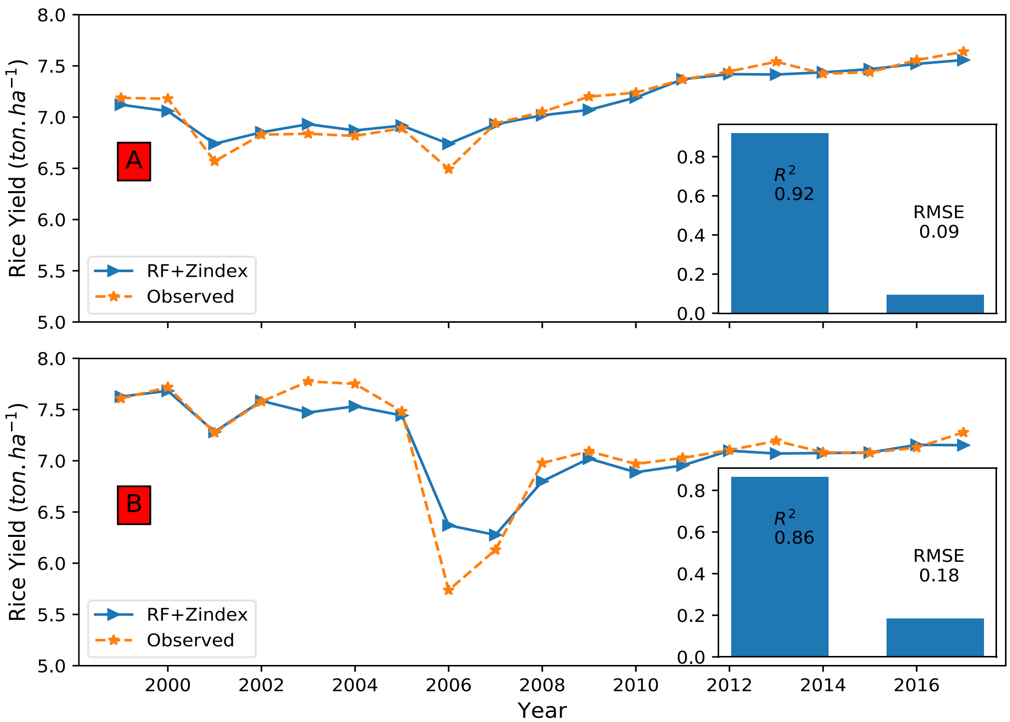

Figure 4. Application of Random Forest plus Z-index for predicting rice yield in Leshan (A) and Dazhou (B). RF represents Random Forest regression. RMSE means Root Mean Square Error.

3.3 Future precipitation and Z-index in Mianyang

Over the next three decades, the annual mean precipitation simulated by the three GCMs under RCP 4.5 tended to decline slightly, while the simulated annual mean precipitation under RCP 8.5 deceased significantly, compared to the 2010s baseline (Figure 5). From Figure 6, the precipitation simulated by three GCMs on decadal time scales were consistent, as they had similar changes in means. In addition, the variation among these simulations became even smaller after the precipitation data were transformed to Z-index.

However, there were some differences among the three GCM simulations. In terms of precipitation, under RCP 4.5, the IPSL_CM5_MR model simulated the highest annual mean precipitation as well as the highest variation of precipitation throughout the 2020s-2040s. On the other hand, CESM1_CAM5 simulated the median annual mean precipitation and the smallest variation of precipitation throughout the 2020s-2040s. Under RCP 8.5, small precipitation variations were seen in 2020s for all three GCMs. However, larger precipitation variations were seen in the 2030s, and 2040s. The Z-index under RCP 4.5, CESM1_CAM5 had the smallest negative aggregate Z-index spread in the 2040s, while IPSL_CM5_MR had the highest negative aggregate Z-index spread in the 2040s. Under RCP 8.5, the values of the Z-indexes were similar among the three GCMs over the next three decades, however, BCC_CSM1_1_M had the smallest negative aggregate Z-index spread compared to the other two GCMs in the 2020s.

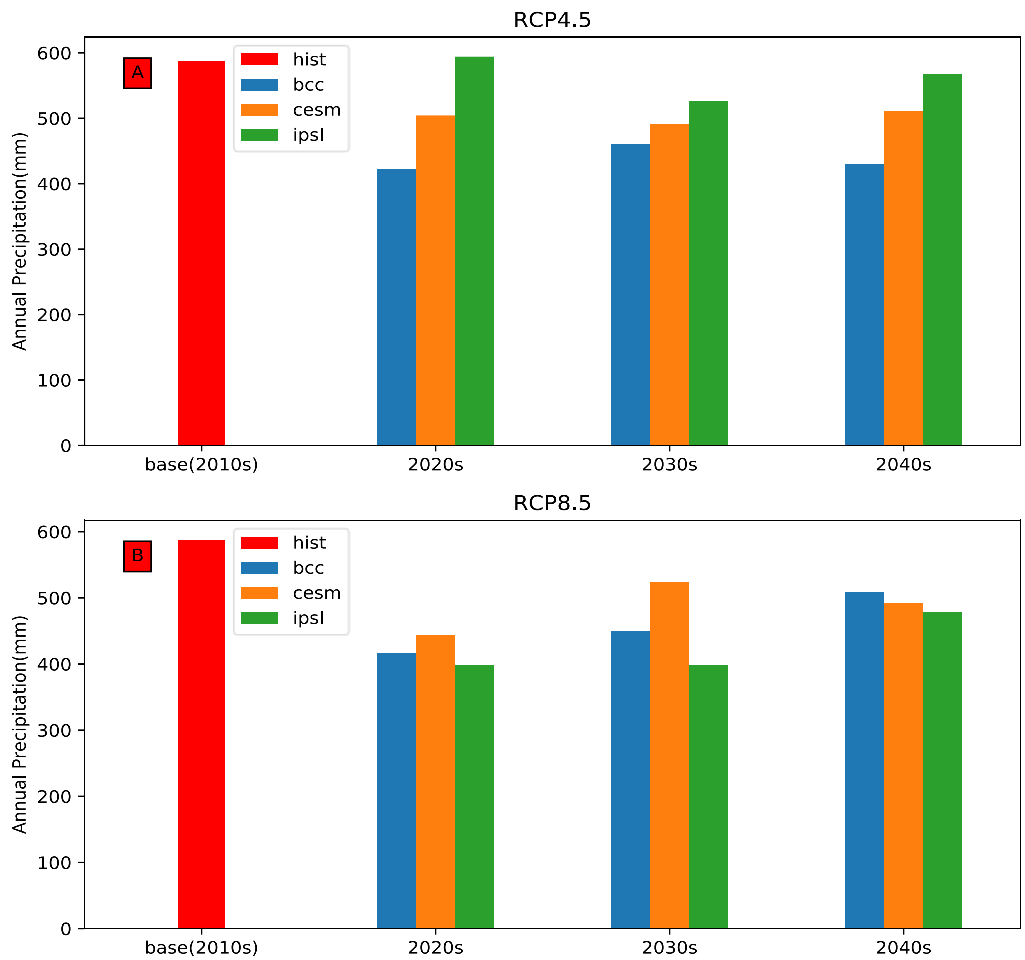

Figure 5. Precipitation in the growing season of rice and maize in Mianyang prefecture. A is the future annual mean precipitation simulated by three Global Climate Models from 2020 to 2050 under RCP4.5, while B is under RCP8.5. 'bcc' means data simulated by BCC_CSM1_1_M, likewise, 'cesm' = CESM1_CAM5, 'ipsl' = IPSL_CM5A_MR. 'hist' means data obtained from history.

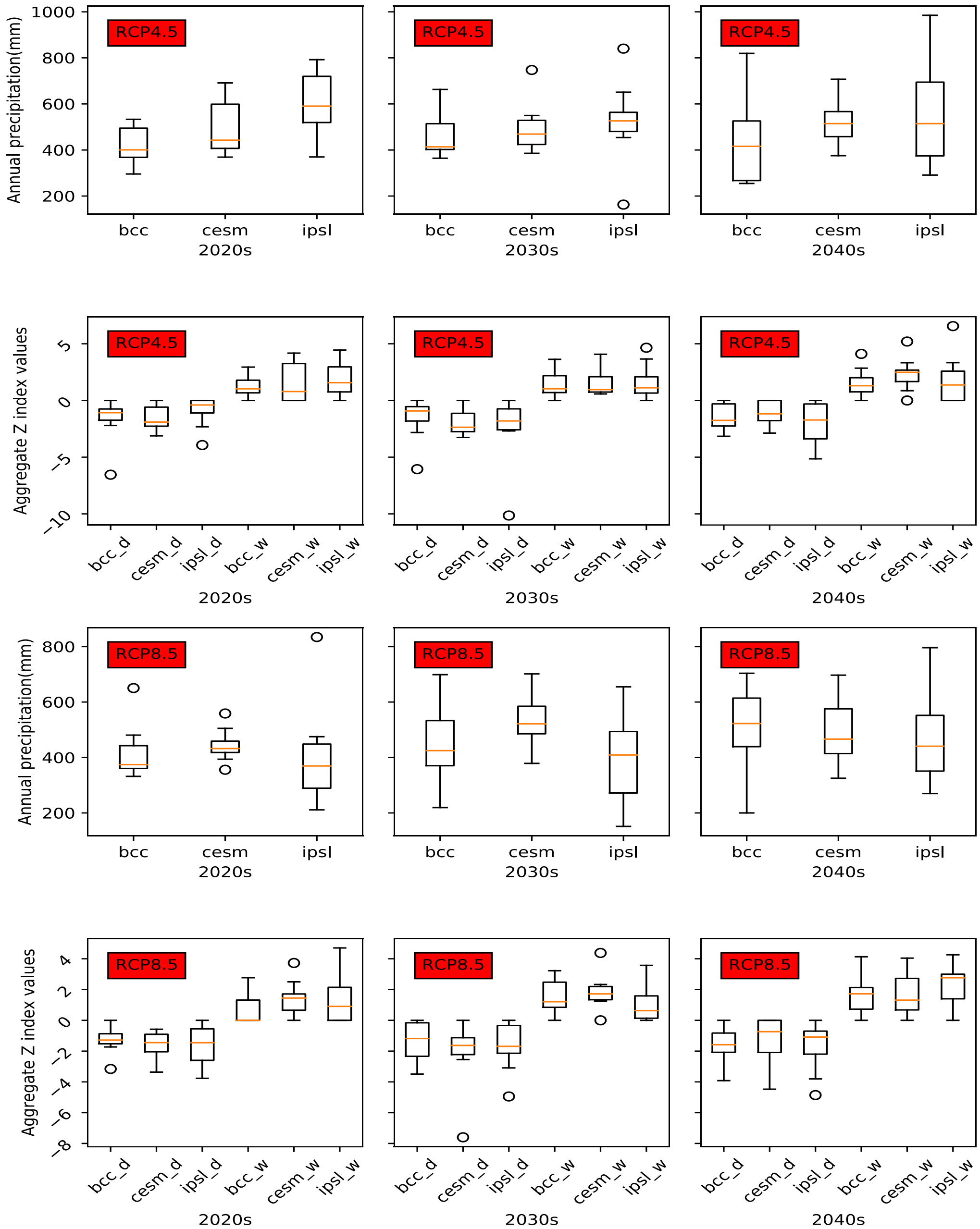

Figure 6. Consistency of future precipitation and Z-index derived from Global Climate Models in Mianyang prefecture. 'bcc' means data simulated by Global Climate Model BCC_CSM1_1_M. Likewise, 'cesm' = CESM1_CAM5, 'ipsl' = IPSL_CM5A_MR. Negative Z-index values represent dry events, while positive Z-index values represent wet events. 'bcc_d' means dry events based on BCC_CSM1_1_M, and 'bcc_w' means wet events based on BCC_CSM1_1_M. So 'cesm_d', 'cesm_w', 'ipsl_d', and 'ipsl_w' have similar meanings.

3.4 Future crop yield variations in Mianyang under climate scenarios

Predicted future crop yields were compared to the base line (2010s). Generally, future crop yields were likely to decline throughout the 2020s-2040s under both the RCP 4.5 and RCP 8.5 climate scenarios, with rice yield reductions larger than maize yield reductions (Figure 7). Under RCP 4.5, the average maize yields tended to decline by -0.27%, -0.65%, and -0.82% in the 2020s, 2030s, and 2040s, respectively. A similar pattern was seen in rice yield reduction, with average rice yields decreasing by -0.93%, -1.59%, and -1.94% in the 2020s, 2030s, and 2040s, respectively. An abnormal case was noted in the 2040s, with maize and rice yields slightly increased based on CESM1_CAM5. Under RCP 8.5, the average maize yields were likely to decrease by -0.69%, -0.64%, and -0.91% in the 2020s, 2030s, and 2040s, respectively, while the average rice yields would drop by -0.95%, -1.23%, and -1.72% in the 2020s, 2030s, and 2040s, respectively. Again, one special case was recorded in the 2020s, when rice yield increased by a small proportion using the simulation data from BCC_CSM1_1_M.

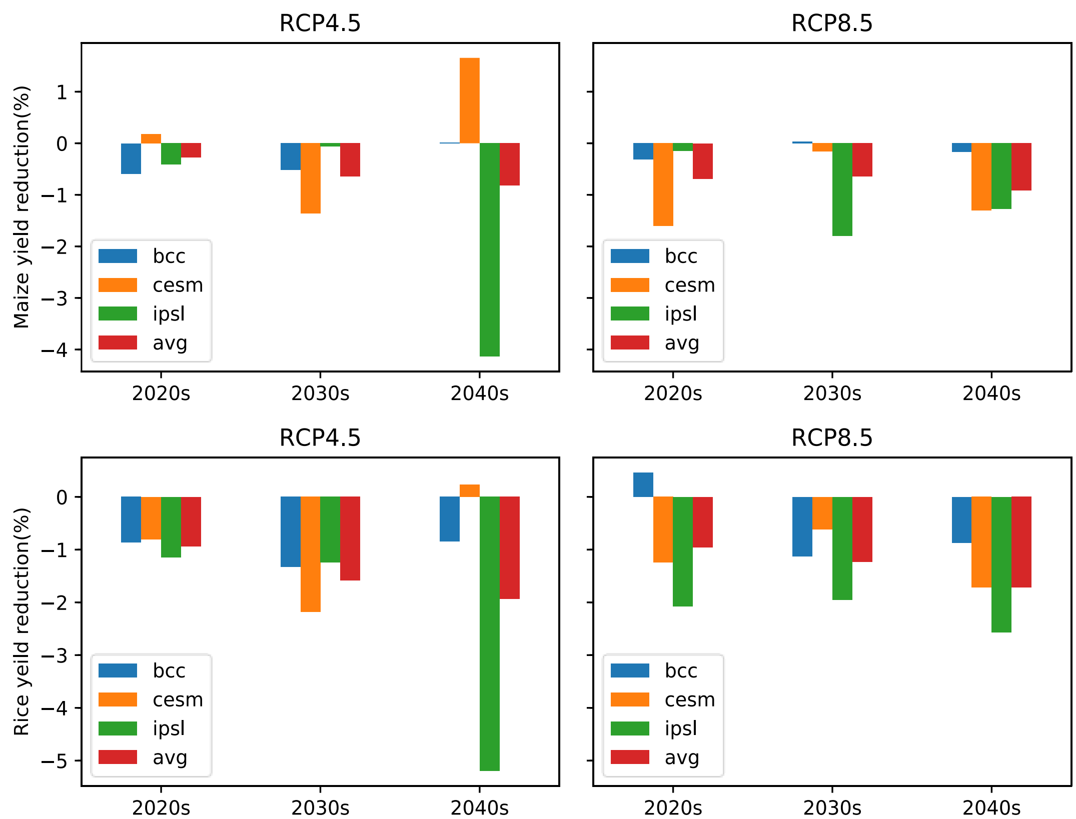

Figure 7. Future rice and maize yield variations compared to the base line period (2011-2017) under climate scenarios RCP4.5 and RCP8.5 in Mianyang prefecture. 'bcc' means yield variations using the precipitation data that simulated by Global Climate Model (GCM) BCC_CSM1_1_M as input. Similarly, 'cesm' = CESM1_CAM5, 'ipsl' =IPSL_CM5A_MR, and 'avg' means the average of yield variations based on those three GCMs.

3.5 Results interpretation

By coupling the aggregate Z-index and RF regression, a new and reliable assessment tool was created for studying and assessing the impacts of extreme precipitation events on rice and maize yields at the local administrative organization level. RF regression does not need careful normalization of input variables or extensive parameter tuning, which makes it easy for other non-professionals to use. Another advantage of RF regression is that variable collinearity does not affect its ability [32]. Moreover, this assessment tool does not require the conduction of long-term experiments, thus making it more efficient to use. This method can be applied to other crops and other locations if training data is provided.

In this study, RF regression outperformed MLR and SVM regression. This was consistent with the studies by Jeong *et al*. [32] and Feng *et al*. [33]. The main reason is that RF is a decision tree-based algorithm. Therefore, it has the ability not only to capture non-linear relationships but also to capture extreme cases. For example, 1994 was an extreme dry year and the RF model was able to simulate the extreme small yield value. Other methods may not have simulated this situation. SVM regression and MLR had similar results in this study because the input variables had some linear relationship with the output variables, and therefore, the kernel parameter was tuned as 'linear' in the SVM model to transform the input data, making it similar to MLR. Using the aggregated Z-index as input to train models was better than using the accumulated precipitation because the Z-index could account for both drought and flood, while accumulated precipitation might have ignored some events due to an uneven precipitation distribution. For example, 2001 is a normal year for accumulated precipitation (Figure 2B), but the aggregated Z-index (Figure 2A) portrays it as a dry year, with corresponding to significantly reduced crop yield.

The Z-index was able to be accurately used to capture the extreme dry and wet events during the historic period, which is consistent with a previous study [23]. The RF+Z-index model indicates that drought affects the crop yield significantly in Mianyang. This is because water is essential in the photosynthesis process, turgidity, solvent nutrients, medium bio-chemical process, and other crop growing processes, so insufficient water may affect these processes and eventually affect crop yield [34]. Time also contributes to the crop yield variation through technology change and management improvements [32, 35]. Flood may affect the respiration of the crop and harm the crop roots, leading to yield loss. However, flood in Mianyang only contributes a small proportion of crop-yield variation. This study implies that drought is more critical for rice yield variation than for maize yield variation. This is mainly due to maize being classified as a C4 crop, which means it is more resilient to drought than rice, which is classified as a C3 crop [36]. Indeed, predicted future yield variations under climate scenarios revealed that maize yield reduction was smaller than rice yield reduction in Mianyang prefecture.

The three GCMs were used to simulate the future precipitation, and the mean change in precipitation predicted was consistent on decadal time scales, especially when the precipitation was transformed to a Z-index. The average future crop yields were decreasing over the next three decades compared to the baseline period. Similar decreasing patterns were reported in the study of Xu *et al*. [16] in Sichuan province using crop models, although their results showed larger reductions. This indicates that our assessment tool can be used as an alternative for local policy makers and other researchers. The abnormal yield increases in the 2040s based on CESM1_CAM5 under RCP 4.5 were due to an annual average aggregate negative Z-index value of -1.12, which was smaller than the other two GCMs' results and suggests that droughts were not that strong. The predicted rice yield increased, while maize yield decreased in the 2020s based on BCC_CSM1_1_M under RCP 8.5, possibly due to the different patterns between historic rice yield and historic maize yield in the training datasets.

3.6 Limitations and future research

Using the Z-index and time as input, RF regression assessed the yield variation impacted by extreme dry and wet conditions. However, the predicted future yield might not be accurate, as it is beyond the training data's boundary. If we want to improve yield prediction, an improved Machine Learning method (for example, combined RF and Linear models) and more relevant input variables are needed. These variables could be technical variables such as research investment and innovations, natural variables such as land quality, and social variables such as social learning platform, labor education and policy intervention at the local level. Moreover, since the Z-index assumes that the precipitation follows a statistical distribution, if the precipitation samples are too small it may not satisfy this assumption and lead to a biased result. Therefore, other users should use the Z-index for future projections with caution. This study had 33 years of precipitation records for all three study areas; however, the longer the record, the more robust the result [37].

In addition, future studies should focus more on specific local variables, and those variables should be modified appropriately (as was done in this study when we used the aggregate Z-index rather than raw precipitation data), and then be inputted into the Machine Learning models. Our future yield variation prediction was heavily based on the GCMs, although we had used three GCMs from different countries and institutions to capture plausible errors and analyzed their consistency. There could be some modifications that might improve our predictions, since projection of future precipitation is so complex, and the confidence of precipitation estimation is smaller than for other climate variables such as temperature [38]. Future research at the local level needs national and international cooperation and research collaboration in the areas of climate change, agriculture, food security, sustainable livelihood, and ecosystem improvement. The establishment of well-organized research infrastructures and a collaboration network to implement these tools needs both private and public support in China and at the global level.

4. Conclusions

The aggregate Z-index accurately captured extreme dry and wet events. The Random Forest regression model was determined to be a good method to assess the impact of extreme events on crop yield. This assessment approach was applicable in different places and showed how crop yield was affected by drought and flood and varied over plant variety, time, and place. The Z-indices derived from three GCMs provided consistent results for predicting future yield variations. In Mianyang prefecture, under climate scenario RCP 4.5, maize yields were likely to decrease by -0.27 to -0.82% and rice yields by -0.93 to -1.94%, compared to the baseline period, over the next three decades. Similarly, under RCP 8.5, maize yields and rice yields could decrease by -0.64 to -0.91% and -0.95 to -1.72% respectively compared to the baseline period, over the next three decades. Both the Z-index and Random Forest model were simple and practical to use for decision makers and practitioners at the prefecture level to gain understanding of the relationships between crop production and extreme events, and to facilitate policy adjustment for local adaptation.

5. Acknowledgements

We thank the China Academic of Agricultural Engineering and Research Program on Climate Change, Agriculture and Food Security for supplying the historic and future precipitation data. We express our appreciation to Dr. Jack Katzfey, CSIRO Australia, for his technical and language editing. We also acknowledge the work of three anonymous reviewers and editorial staff, who provided valuable suggestions, attention, and time.

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