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Effect of Climate Change on Staple Food Production: Empirical Evidence from a Structural Ricardian Analysis

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Abstract: The structural Ricardian model has been used to examine the links between climate variables and staple food production in the literature. However, empirical extensions considering the cluster-correlated effects of climate change have been limited. This study aims to bridge this knowledge gap by extending the structural Ricardian model to accommodate for spatial clustering of the climate variables while examining their effects on staple food production. Based on nationally representative farm household data in Taiwan, the present study investigates the effect of climate conditions on both crop choice and the subsequent production of the three most important staple foods. The results suggest that seasonal temperature/precipitation variations are the major determinants of staple food production after controlling for farm households' socio-economic characteristics. The impacts of seasonal climate variations are found to be location-dependent, which also vary significantly across the staple food commodities. Climate change impact assessment under four Representative Concentration Pathways (RCPs) scenarios indicates the detrimental effect of climate change on rice production during 2021–2100. Under RCP6.0, the adverse effect of climate change on rice production will reach the high of approximately $2900 in the last two decades of the century. There is a gradual increase in terms of the size of negative impact on vegetable production under RCP2.6 and RCP4.5. Under RCP6.0 and RCP8.5, the effects of climate change on vegetable production switch in signs during the entire time span. The impact of climate change on fruits is different from the other two staple foods. The simulated results suggest that, except for RCP8.5, the positive impact of climate change on the production of fruits will be around $210–$320 in 2021–2040; the effect will then increase to $640–$870 before the end of the century.

Keywords: climate change impact assessment; crop choice; staple food production; structural Ricardian model; clustered-data analysis

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1. Introduction

The effect of climate change on crop production or productivity has been subject to substantial scrutiny in the literature since the first rigorous assessment in the 1975 Climate Impact Assessment Project [1,2]. Although most early studies of climate change assessment focused on the US and Europe [2], there is emerging interests in assessing the impact of climate change on agriculture for developing countries, for example, [3–9], since the tropical and subtropical regions are projected to be affected to the greatest extent [10–12]. Through an examination of the impact of climate change from a global perspective, some authors [13–15] suggested the impact of climate change varies with the latitude of the targeted regions. It was noted that climate impact assessment based on a global scale suffered under the exploration of spatially specific nature of the data and aggregations that smoothed out spatial variations within a region or country [14]. In light of the lack of empirical evidence from a country-specific study, there were a few studies, for example, [16–28], that assessed the impacts of climate change based on a micro-level (farm or farm household) analysis.

Drawn from nationally representative farm household data in Taiwan, the present study aims at examining the effect of climate variables, including temperature and precipitation, on the production of the three most important staple foods: rice, vegetables and fruits. The use of farm household data in Taiwan for climate change impact assessment is relevant, since more than 98% of the 721,224 farm households who engaged in agriculture production in Taiwan are growers of crops including rice, vegetables, fruits, specialty crops, grains and other crops [29]. Examination of the effect of climate change on food production in Taiwan can provide solid evidence and a significant complement to the existing body of knowledge.

The contribution of the present study is three-fold. First, most of the country- or region-specific studies in Asia are targeted at South Asian countries. Insufficient evidence of the effect of climate change on Northeast Asian agriculture accentuates the need to explore the impacts of climate change in the region. Second, one common characteristic of most northeast Asian countries is their structure, with the majority of farms being small in scale [30]. Taking Taiwan as an example, the average size of the farmland is approximately 1.02 hectares according to the most recent statistics. Empirical evidence supporting the climate effect on Taiwan's staple food production provides a significant complement to the scant literature on the losses or gains of smallholder farms in their process of adaptation to climate change. Third, Taiwan is characterized by clear spatial and seasonal variations in temperature and rainfall. There are two distinct climatic characters on the island: "the tropical monsoon climate in the south and subtropical monsoon climate in the north" [31]. This study, therefore, can advance our understanding of how the impact of climate change varies with seasonal or spatial variability within a country.

The major research problem this study attempts to address is: What are the effects of climate change on farm households' production of staple foods of various kinds? To this end, we base our analysis on the structural Ricardian model [32]. The Ricardian or structural Ricardian models have been used to examine the effect of climate change, addressing the production-related effects of current climatic conditions and a long-term projection or simulation of the effect of climate change [27,28,33–42]. However, empirical extensions to considering the cluster-correlated effect of climate on food production have been limited. This study aims to bridge this knowledge gap by extending the structural Ricardian model to accommodate for spatial clustering of the climate variables while examining their effects on staple food production.

The remainder of this paper is as follows. Section 2 presents the spatial variations in climate variables and the distribution of the three staple foods in Taiwan. Section 3 delineates the 2015 Census of Agriculture, Forestry, Fishery and Animal Husbandry data (in short, 2015 Agriculture Census data) and the structural Ricardian model. Following Section 3 are the results and discussion. The final section summarizes the major findings and possible future extensions of the present research.

2. Spatial Distribution of Staple Foods and Climatic Variations

The spatial distribution of the three staple foods are different (Figure 1). Rice is more concentrated in the coastal area of central and central-south counties. Among the top three counties, the first two are located in central Taiwan while the third is located in the south. The largest county in the central area, Nantou county, is an inland county which takes a relatively small share of total rice production in Taiwan. Although vegetables are also more concentrated in central Taiwan, the counties in the top club tend to be located more in the south when compared to the top club of rice. Among the top three counties producing vegetables, one is in the central area while the other two are in the south. The spatial distribution of fruits is mainly concentrated in southern Taiwan. The top three counties producing fruits are all in the south. A comparison of the spatial distribution of rice, vegetables and fruits indicates a shift from north-central to central and south.

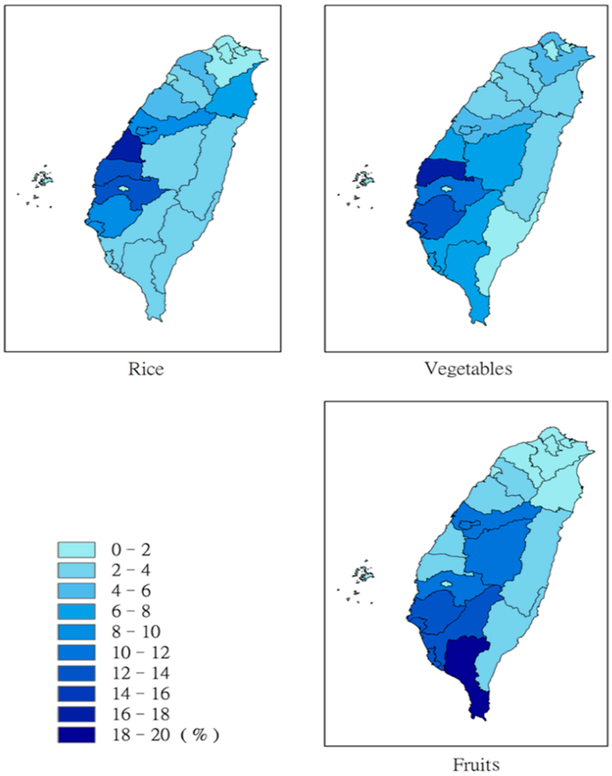

Figure 1. Spatial distribution of rice, vegetables and fruits.

The temperature in Taiwan has been rising by about 1.3 °C in the past 100 years, which is projected to rise by 1.3–1.8 °C under the representative concentration pathway (RCP) 4.5 scenario, and may reach the high of a 3.0–3.6 °C surge at the end of this century under an RCP 8.5 scenario [43]. On average, there is a mild spatial difference in temperature; the annual temperature in southern Taiwan is about 24 and 22 °C in the north [31]. In contrast to the mild spatial variations in temperature, the variations in precipitation are more obvious (Figure 2).

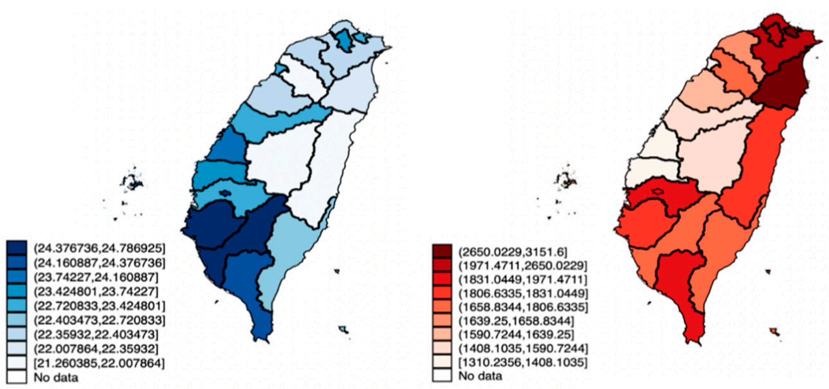

Figure 2. Spatial climatic variations (**left panel**: temperature; **right panel**: rainfall).

Taiwan lies between the Eurasian and the Pacific, and thus the seasonal variations in rainfall are mainly affected by the Siberian High and Pacific Subtropical high and its accompanying circulation and weather system [44]. The wet season in Taiwan starts from May to October, which is followed by the dry season, until 1 April the following year. During the dry season, the rainfall in central and southern Taiwan decreases rapidly from October, whereas there is still considerable rainfall in the north and east of the windward side [45].

3. Materials and Methods

3.1. Data and Descriptive Statistics

The data used in the present research are taken from the 1% sampling data from the 2015 Agriculture Census data, which was recently released by the Executive Yuen in Taiwan. According to the description of the Directorate General of Budget, Accounting and Statistics [29], the 1% sampling data of the 2015 Agriculture Census is randomly sampled from a total of 845,241 farm households, resulting in 6950 farm households in total. After deleting the farm households whose major farm operation is livestock or who did not engage in farming for land use, the data of farm households number 5315. We focus on the farm households producing the three staple foods, rice, vegetables and fruits, which comprise around 85% of the farm households producing mainly crops. According to the codebook of 2015 Agriculture Census Survey, the fruits and vegetables included in the two food groups are listed in Appendix A (Table A1). The final dataset contains a sample size of 4487 farm households. Descriptions and descriptive statistics of the dependent and explanatory variables are listed in Table 1. Note that most of the farm households produce more than one crop; classification of the single staple food commodity is defined in terms of the crop taking the largest share in total production value.

Table 1. Variable definition and descriptive statistics.

Variable	Definition	Mean	Std Dev
Outcome			
Production Value	Production value (National Taiwan Dollar, NTD, per unit farmland) of major crop	3608.729	4836.03
Crop choice			
Rice	Crop (rice)	0.459	0.50
Vegetables	Crop (vegetable)	0.213	0.41
Fruits	Crop (fruit)	0.329	0.47
Principal operator's characteristics			
Male	Gender of the principal operator	0.806	0.40
Age1	Age (45–54 years old)	0.050	0.22
Age2	Age (55–64 years old)	0.198	0.40
Age3	Age (55–64 years old)	0.299	0.46
Age4	Age (65–75 years old)	0.250	0.43
Age5	Age (more than 75 years old)	0.204	0.40
Elementary	Education (elementary school and below)	0.445	0.50
Junior high	Education (junior high school)	0.236	0.42
Senior high	Education (senior high school)	0.245	0.43
College	Education (college and above)	0.073	0.26
Exp1	Farm experience (less than 5 years)	0.090	0.29
Exp2	Farm experience (5 to less than 10 years)	0.118	0.32
Exp3	Farm experience (10 to less than 20 years)	0.212	0.41
Exp4	Farm experience (more than 20 years)	0.580	0.49
Days1	On-farm work (less than 60 days)	0.417	0.49
Days2	On-farm work (60–149 days)	0.381	0.49
Days3	On-farm work (equal to or greater than 150 days)	0.202	0.40
HH (Household) characteristics			
HH size	Household size (persons)	3.664	2.06
HH labor	Household members working on the farm (%)	0.638	0.29
Land	Farmland used for crop production (are)	76.739	89.02

Due to high correlations of monthly climate data (Table 2), the seasonal averages in temperature and precipitation are used to capture the effects of climate on crop choice and production of the three staple food commodities. The four seasons are defined as: spring

(March, April, May), summer (June, July, August, September), fall (October, November) and winter (December, January, February). It was indicated that summer is one month longer than before in Taiwan [43]. Therefore, summer is composed of four months in the present study.

3.2. Research Design

The effect of climate variables on staple food production is modeled in a two-stage framework as in previous studies, for example, [33,34,38,40]. The two-stage modeling is a generalization of the selection correction model [46]. In stage 1, the farm household's choice of a staple food to produce is based on the random utility theory and estimated through a multinomial logit (MNL) model. The second stage incorporates the selection-bias correction terms into the explanation of the production value of staple foods.

According to the random utility model [47,48], the choice of crop results from the comparison of indirect utility associated with different choices by the decision unit, which is the farm household in our case. There are three crops considered in this study: rice, vegetable and fruit. Let the indirect utility associated with the choice of the mth crop be denoted by U_m^*, where m = 1 denotes rice, m = 2 denotes vegetables and m = 3 denotes fruits. The choice of the sth crop can be expressed as

$$U_s^* > \max_{m=1,2,3,m\neq s} U_m^* \quad (1)$$

Previous studies based on the Ricardian approach confirmed the influential role of climate variables in crop choice, for example, [34,37,49,50]. The indirect utility is thus further assumed to be a linear function of the characteristics of the farm, farm households and principal operators as well as the climate variables

$$U_m^* = \mathbf{W}\boldsymbol{\alpha}_m + \mathbf{X}\boldsymbol{\beta}_m + \eta_m,\ m = 1,2,3 \quad (2)$$

In the above equation, $\mathbf{W}$ and $\mathbf{X}$ are, respectively, the vector of climatic conditions and the vector of socio-characteristics. $\boldsymbol{\alpha}_m$ and $\boldsymbol{\beta}_m$ are the vectors of parameters and η_m is the random disturbance terms. It is assumed that the difference in the indirect utility between the crop chosen (s) and that not chosen ($m \neq s$) can be expressed as

$$\begin{aligned} \varepsilon_s &= \max_{m\neq s}(U_m^* - U_s^*) \\ &= \max_{m\neq s}(\mathbf{W}\boldsymbol{\alpha}_m + \mathbf{X}\boldsymbol{\beta}_m + \eta_m - \mathbf{W}\boldsymbol{\alpha}_s - \mathbf{X}\boldsymbol{\beta}_s - \eta_s) \end{aligned} \quad (3)$$

According to (1), the difference between the indirect utility of crop choices defined in (3) is less than zero, and the conditional probability of the choice of the sth crop is equal to the conditional probability of negative utility difference.

Following previous research, the choice of the three staple foods is basically unordered in nature, and thus is estimated through the MNL model under the assumption that $(\varepsilon_{i1}, \varepsilon_{i2}, \varepsilon_{i3})$ follows a multinomial logistic distribution. Let the indicator variable, D_s, take the value of 1 when the sth crop is chosen and 0 otherwise. The probability that the ith farm operator chooses the sth crop can be expressed as

$$\mathrm{Prob}(D_s = 1 \mid \mathbf{X}, \mathbf{W}) = \frac{\exp(\mathbf{W}\boldsymbol{\alpha}_s + \mathbf{X}\boldsymbol{\beta}_s)}{\sum_{m=1}^{3} \exp(\mathbf{W}\boldsymbol{\alpha}_m + \mathbf{X}\boldsymbol{\beta}_m)} \quad (4)$$

The MNL model can be estimated through the following log-likelihood function:

$$L = \sum_{i=1}^{N} \sum_{m=1}^{3} D_{im} \cdot \log[\mathrm{Prob}(D_m = 1 \mid \mathbf{X}_i, \mathbf{W}_i)] \quad (5)$$

Note that in the likelihood function in (5), the N observations are clustered into c clusters for each of the climate variables to take into account the spatial correlation of the observations located at the same cluster.

Possible correlation between crop choice and the production value of the crop is corrected by including three selection correction terms into the production-value-determination equation [47]. The effect of the climate variables on the production of the sth staple food commodity is then estimated as the following

$$E(Y_i \mid D_s = 1) = \mathbf{Z}_i \boldsymbol{\gamma}_s + \mathbf{W}_c \boldsymbol{\kappa}_s + \sigma \cdot \sum_{i \neq m}^{3} r_i \cdot \left(\frac{P_i \cdot \ln P_i}{1 - P_i} + \ln P_m \right) \quad (6)$$

where Y_i denotes the production value of the sth commodity produced by the ith farm household, which is located in county c; $\mathbf{Z}$ is the explanatory variables affecting the production value of the sth commodity other than the climate variables. The vectors of parameters are denoted by $\boldsymbol{\gamma}$ and $\boldsymbol{\kappa}$, respectively. It is important to note that there is assumed independence across clusters (counties) but correlation within clusters (counties).

4. Results

4.1. The Choice of Crop Commodity

Coefficients for the stage 1 (MNL) model of the farm household's choice of the three staple foods are obtained through the estimation of the likelihood function specified in Equation (5). Table 2 reports the estimates of the MNL estimate with the rice households as the reference group while controlling for the climatic conditions and the socio-economic characteristics of the principal operator or the farm household. The estimates of crop choice reported in Table 2 are interpreted in a relative sense, i.e., the coefficient of one predictor in the kth crop choice is a measure of the effect of the predictor on the probability of choosing the kth crop over the reference group. We estimate two different specifications in Table 2. The first four columns are the MNL model estimates, controlling only for seasonal temperature and precipitation conditions.

The results in Table 2 are, in general, unsatisfactory, since only one coefficient is a significant determinant of the choice of vegetables relative to rice. The last four columns control for both the climatic conditions and the socio-economic characteristics of the principal operator and the farm household. After controlling for the socio-economic characteristics, the structural Ricardian model estimates are more satisfactory in terms of the individual significance of the climate variables and their squared terms. Therefore, in the following analysis, we calculated the selection correction terms according to the estimates reported in columns 5 and 7 in Table 2.

According to the results in Table 2, the principal operator's socio-economic characteristics, including age, educational level, years of farming experience and on-the-farm workdays, are important determinants for their choice of staple food commodities. Additionally, seasonal average temperatures and their squared terms, and seasonal average precipitation and their squared terms, are the major determinants of staple food production in Taiwan. The results suggest the nonlinear effect of seasonal average temperature and precipitation on the farm household's choice of staple food commodity.

Table 2. Maximum likelihood estimates of the multinomial logit (MNL) model.

Variable	Vegetables			Fruits			Vegetables			Fruits		
	Coef.		**S.E.**	**Coef.**		**S.E.**	**Coef.**		**S.E.**	**Coef.**		**S.E.**
Seasonal temp												
Spring	−5.5771		18.38	−20.8146	***	2.95	−11.0578		13.98	−26.2727	***	4.83
Summer	10.4691		9.92	−18.5363	***	2.28	17.4990	**	7.31	−12.8134	***	3.15
Fall	−7.5452		5.67	3.5163	***	1.06	−8.0489	*	4.11	0.6089		2.40
Winter	10.7260		12.11	12.1159	***	2.34	11.2718		8.97	14.3472	***	3.46
Temperature sq												
Spring	0.1546		0.44	0.5614	***	0.08	0.2706		0.34	0.6885	***	0.12
Summer	−0.1775		0.15	0.2592	***	0.03	−0.2784	**	0.11	0.1684	***	0.05
Fall	0.1071		0.12	−0.0017		0.03	0.0802		0.09	0.0302		0.05
Winter	−0.3248		0.40	−0.4788	***	0.08	−0.3206		0.29	−0.5292	***	0.11
Seasonal rainfall												
Spring	−0.0487		0.06	−0.1864	***	0.01	−0.1200	***	0.05	−0.2563	***	0.03
Summer	−0.0379		0.04	−0.0571	***	0.01	−0.0354		0.03	−0.0655	***	0.01
Fall	0.0035		0.01	0.0345	***	0.00	0.0010		0.01	0.0302	***	0.00
Winter	0.0540		0.07	0.0514	**	0.02	0.0569		0.05	0.0877	**	0.04
Rainfall sq												
Spring	0.0001		0.00	0.0006	***	0.00	0.0004	**	0.00	0.0009	***	0.00
Summer	0.0001		0.00	0.0001	***	0.00	0.0001		0.00	0.0001	***	0.00
Fall	−0.0001	*	0.00	−0.0001	***	0.00	0.0000	**	0.00	−0.0001	***	0.00
Winter	0.0000		0.00	−0.0002	***	0.00	−0.0002		0.00	−0.0005	**	0.00
Socio-economic												
Male							−0.1783		0.12	0.0807		0.07
Age2							−0.2635		0.18	−0.1297		0.16
Age3							−0.5095	**	0.22	−0.4244	**	0.18
Age4							−0.7505	***	0.27	−0.5890	**	0.25
Age5							−0.8833	***	0.23	−0.5617	**	0.25
Junior high							0.0591		0.12	0.1955	*	0.10
Senior high							−0.2021		0.14	0.2049		0.14
College							−0.4661	**	0.18	0.0626		0.23
Exp2							0.0320		0.29	0.3142		0.23
Exp3							0.3825	*	0.20	0.1767		0.19
Exp4							0.2612	**	0.13	0.3214	***	0.11
Days2							0.9957	***	0.21	0.9182	***	0.30
Days3							2.1816	***	0.32	2.0915	***	0.36
Land							−0.0029	***	0.00	−0.0002		0.00
HH size							0.1052	**	0.05	0.0806	**	0.03
HH labor							1.0956	***	0.39	1.0395	***	0.34
_Cons	−71.2235		177	356.805		43.57	−100.1176		134.95	358.1025	***	65.41
No. of obs	955			1474			955			1474		

Note: *, ** and *** denote significant at the 10%, 5% and 1% significance level.

4.2. Estimating the Structural Ricardian Model

Our stage 2 estimation of the structural Ricardian model incorporates the three selection-correction terms into the clustered regression of the per-unit product value. In this stage, the controlled variables include the social–economic characteristics of the farm household and principal operator, seasonal temperatures and the squared terms, and seasonal precipitations and the squared terms. The estimates of the clustered regression conditioned on the farm household's crop choice are reported in Table 3.

Coefficient estimates of the three selection-correction terms are significant for rice farms but not significant for the other two staple food growers. Therefore, results from uncorrected regression of the vegetable and fruit households are reported in columns 3–6 in Table 3. Based on the results in Table 3, seasonal temperatures and precipitations are found to exhibit non-linear impacts on the production of each of the three staple foods.

Table 3. Clustered regression conditioned on choice of staple food commodity.

Variable	Rice			Vegetables			Fruits		
	Coef.		**Std. Err.**	**Coef.**		**Std. Err.**	**Coef.**		**Std. Err.**
Seasonal temp									
spring	99,667.82	*	50,650.42	57,722.10		37,019.12	8649.404		27,169.72
summer	64,089.40	*	31,053.26	29,068.89		19,671.57	13,578.69		15,010.17
fall	−15,822.99	***	4064.56	−57,617.96	***	8740	−39,651.51	***	7140.18
winter	−45,873.56		26,783.95	−11,179.70		18,820.64	1160.545		17,882.19
Temperature sq									
spring	−2630.50	*	1332.38	−1279.33		875.01	−124.7959		681.49
summer	−868.88	*	419.96	−493.95	*	280.6	−260.6547		226.6
fall	58.99		65.69	991.98	***	214.3	719.5156	***	156.83
winter	1834.12	*	1007.98	520.62		609.03	60.359		589.97
Seasonal rainfall									
spring	941.71	*	495.53	−78.87		129.51	−116.4395		126.86
summer	242.24	*	125.04	−52.18		62.22	−69.60886		66.46
fall	−130.16	**	60.95	−43.50	**	19.51	−21.9075		16.3
winter	−377.69	**	172.41	9.22		124.1	190.4126	*	102.68
Rainfall sq									
spring	−3.30	*	1.73	0.17		0.49	0.4660478		0.45
summer	−0.49	*	0.26	0.10		0.11	0.1015217		0.13
fall	0.26	*	0.13	0.05		0.05	0.0248407		0.04
winter	2.10	**	0.95	−0.02		0.32	−1.073143	**	0.39
Selection terms									
Rice	−978.38	*	527.79						
Vegetables	−216.26	*	109.57						
Fruits	1301.23	*	638.22						
Control for socio-econ vars	yes				yes			yes	
_cons	−1,468,703.00	*	757,124.10	−244,460.70			178,770.6		345,465.6

Note: *, ** and *** denote significant at the 10%, 5% and 1% significance level.

5. Discussion

The effect of the climate variables on the choice of major crop to produce is nonlinear, since some of the coefficients for the squared terms are significant (Table 2). The coefficient estimate from the MNL model is not a straightforward measure of the effects, especially when there are squared terms involved. In order to provide a more intuitive description of the impact of climatic conditions on the farm household's crop choice, we present the predictive margin plots by varying each of the climate variables over the whole dataset and calculate the averages of predicted probability for each crop choice. Figures 3 and 4 illustrate the effects of seasonal increases in temperature on the probability of crop choice.

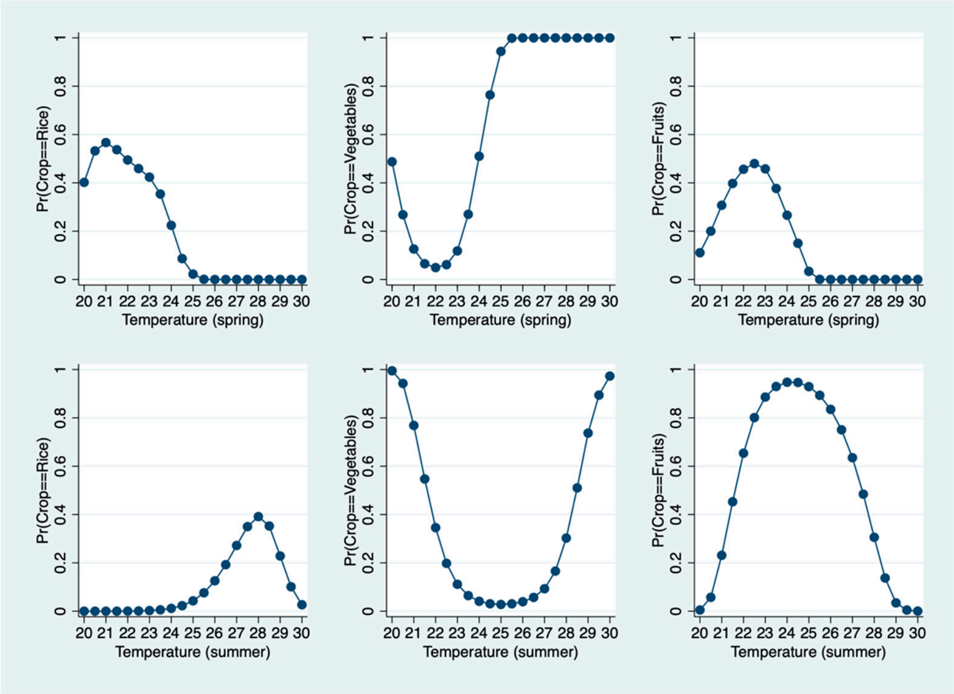

Figure 3. Predictive effect of temperature (spring, summer).

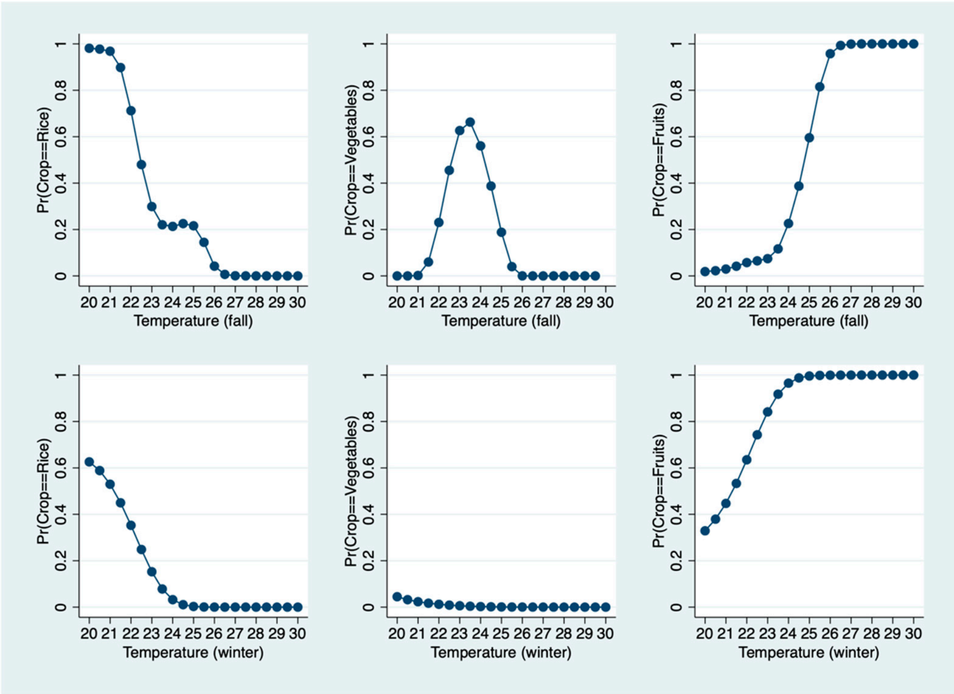

Figure 4. Predictive effect of temperature (fall, winter).

The upper panel of Figure 3 shows that farm households are inclined to produce vegetables when spring is warm. The average temperature in spring is 23.16 °C; when it is 1 °C warmer, more than half of the farm household will choose to produce vegetables. However, the lower panel of Figure 3 reveals that there is a higher probability of choosing to produce fruits when the temperature is below the average (27.74 °C) in summer. Nonetheless, when the temperature is higher than the average, farm households will switch to producing vegetables. Figure 4 illustrates the increasing tendency to produce fruits in the fall (upper panel) and in the winter (lower panel).

The effects of seasonal average precipitations are graphed in Figures 5 and 6. Spring and summer are the wet seasons in Taiwan. The upper panel of Figure 5 indicates that increasing rainfall when it's below the average level of 175 mm in the spring will increase the farm household's probability of producing rice. However, increasing precipitation at higher than average levels in the spring will eventually induce the switch to vegetables.

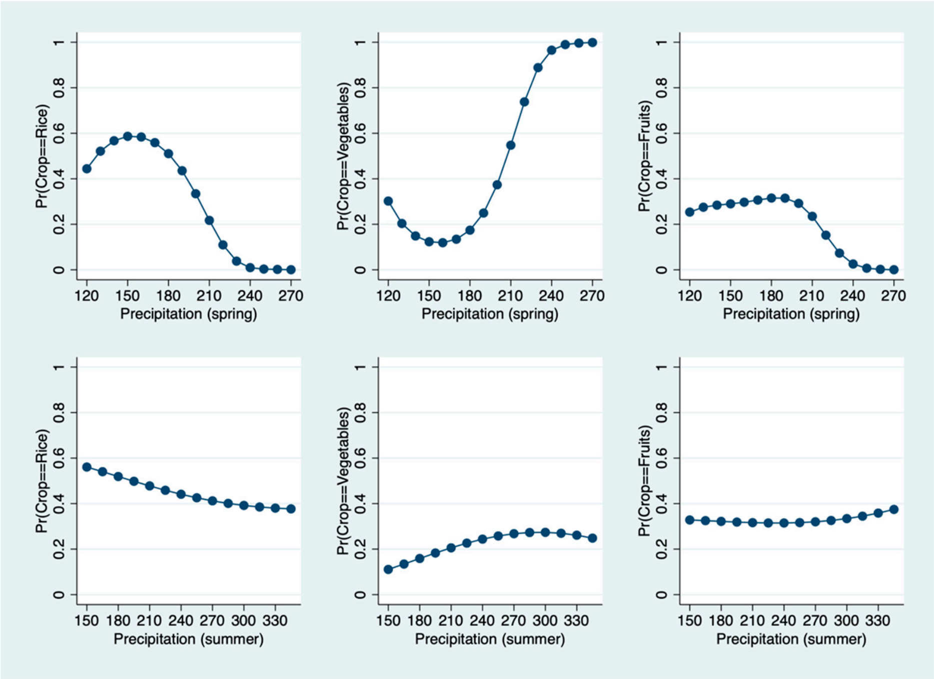

Figure 5. Predictive effect of precipitation (spring, summer).

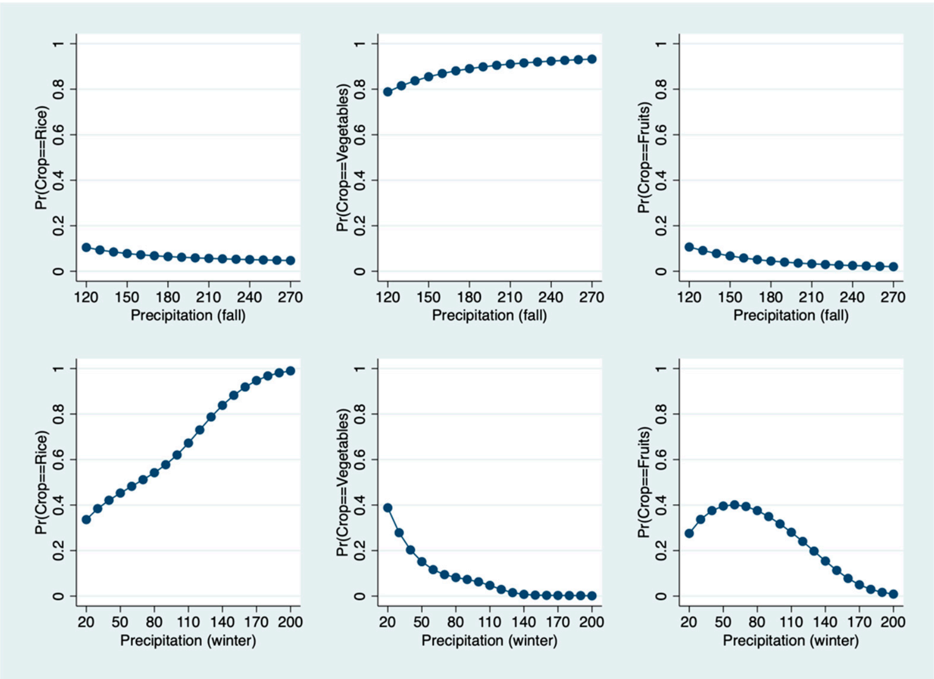

Figure 6. Predictive effect of precipitation (fall, winter).

The lower panel of Figure 5 nonetheless indicates that the probability of crop choice is relatively stable relative to the increase in precipitation in the summer. Figure 6 portrays the effect of increasing precipitation during the dry season (fall and winter) in Taiwan. The choice of vegetables remains dominant in the fall (upper panel), while more rainfall in the winter will persistently increase the farm household's choice of producing rice (lower panel).

In order to predict the effect of variations in climatic conditions on the production value of the staple foods, we report the marginal effects of the climate variables in Table 4. The F-statistic reported in Table 4 is the test for the joint significance of the seasonal temperature (precipitation) and its squared term. According to the estimates reported in Table 4, high temperature in the fall is found to have a unanimous dampening effect on the production of staple foods, which is, in order, −$790 (vegetables), −$430 (rice) and −$50 (fruits). The results suggest the impacts of seasonal temperature variations in general vary significantly across the staple food commodity chosen by the farm household. Among the three staple food crops, vegetables seem to be more sensitive to seasonal variations in temperature. There are two reasons that can explain this result. First, the growth cycles of vegetables are generally shorter than rice and fruits, which may lead to more sensitive responses of vegetables to seasonal temperature variations. Second, based on the farm-household frequency distribution of major commodities in the 2015 Agriculture Census data [51], we calculated the proportion of vegetable households producing mainly leafy vegetables and found that the share of leafy vegetables was around 47%. Since leafy vegetables are relatively more vulnerable to high/low temperatures, another reason to explain why vegetables are more sensitive to temperatures is due to the fact that almost half of the vegetable households produce mainly leafy vegetables.

Table 4. Predicted effects of temperature or precipitation on staple food production (USD per-unit farmland).

Commodity/	Temperature				Precipitation			
Season	Mean		Std. Dev.	F-stat	Mean		Std. Dev.	F-stat
Rice/								
Spring	−712.897		7.22	2.33	−8.135	*	0.19	3.61
Summer	522.128		1.57	2.16	0.604	*	0.06	3.75
Fall	−432.440	***	0.13	8.80	−3.274	**	0.06	5.11
Winter	593.887	***	4.23	9.01	−7.061		0.15	2.47
Vegetables/								
Spring	−2944.631	***	38.49	9.45	−1.044		0.00	1.73
Summer	1163.105		3.82	0.96	−0.051		0.01	0.55
Fall	−792.191	**	0.87	4.48	−1.522	***	0.01	8.53
Winter	2306.079	**	26.45	4.77	0.596		0.00	0.05
Fruits/								
Spring	−278.334		4.26	2.15	1.528		0.03	2.29
Summer	45.317		0.12	0.16	−0.572	**	0.02	6.02
Fall	−46.642	**	1.05	3.98	−0.594		0.00	1.4
Winter	351.390		4.18	0.19	4.495	**	0.05	5.89

Note: 1 USD =30 NTD; *, ** and *** denote significant at the 10%, 5% and 1% significance level.

Taiwan is characterized by clear spatial variations and seasonal variations in rainfall. Similar to the effect of variations in seasonal average temperature, the effect of seasonal precipitation variations is found to vary significantly across the staple food commodity chosen by the farm household. Nonetheless, our results indicate that increasing precipitation in the winter can significantly increase the production of fruits which are heavily concentrated in southern Taiwan.

A comparison of the three staple food commodities indicates that, among the three staple foods, vegetable production is found to be affected by high temperatures to the largest extent. Although the negative impact of high temperature in spring and fall may be partly offset by the positive effect of higher temperature in winter, vegetables are the most vulnerable to the variations in seasonal average temperature among the three crops. As for the effect of precipitation, we found that rice production is influenced to the greatest extent, due to increasing precipitation in the spring.

To assess the impact of climate change on staple foods production, we perform simulation analysis under four Representative Concentration Pathways (RCPs) scenarios. The four scenarios in Table 5 (RCP2.6, RCP4.5, RCP6.0 and RCP8.5) are projected change in climate parameters for Taiwan during the time period of 2021–2100, based on IPCC AR5 (the Fifth Assessment Report of the Intergovernmental Panel on Climate Change) [52].

Table 5. Scenarios of climate change.

Year	Area	Change in Temperature (°C)				Change in Precipitation (mm)			
		RCP2.6	RCP4.5	RCP6.0	RCP8.5	RCP2.6	RCP4.5	RCP6.0	RCP8.5
2021–2040	North	0.64	0.68	0.61	0.78	41.1	47.1	36.6	78
	Central	0.64	0.68	0.62	0.78	45.3	55.8	54.9	102.9
	South	0.62	0.66	0.62	0.76	48.9	56.4	49.2	119.1
	East	0.62	0.65	0.61	0.76	49.2	38.1	34.8	82.5
2041–2060	North	0.95	1.17	0.94	1.51	124.8	111.6	3.3	27.9
	Central	0.93	1.15	0.94	1.5	127.8	123	−37.5	21.3
	South	0.9	1.13	0.92	1.46	148.8	134.7	−222.3	22.5
	East	0.91	1.13	0.91	1.46	120.6	104.4	−99.3	21.3
2061–2080	North	0.89	1.47	1.43	2.36	141.6	147.3	49.8	71.7
	Central	0.88	1.45	1.43	2.32	147	152.1	69.3	83.1
	South	0.86	1.41	1.40	2.27	142.2	150.9	68.4	99.6
	East	0.86	1.41	1.39	2.27	128.4	125.1	60.3	70.2
2081–2100	North	0.77	1.57	1.98	3.16	154.8	108.9	125.4	49.8
	Central	0.78	1.56	1.96	3.1	161.7	124.8	150	39.3
	South	0.26	1.52	1.91	3.03	144.6	132.9	143.1	54.9
	East	0.76	1.52	1.91	3.04	120.9	96.6	122.7	52.8

RCP2.6 is a scenario with global warming making very mild progress, and thus the scenario with the least increase in temperature and the largest scale of rainfall increase. A relatively modest progression of global warming is projected under RCP4.5 and RCP6.0. Relatively speaking, RCP6.0 has a larger scale of temperature increase compared to RCP4.5, especially in 2081–2100. On the other hand, precipitation is projected to increase steadily under RCP4.5, whereas there is a decrease in precipitation, ranging from −37.5 to −222.3 mm in 2041–2060, and a mild increase in the following two decades under RCP6.0. RCP8.5 is the scenario with the most severe progression in global warming. Under RCP8.5, the temperature increases to the largest extent, while there seems to be some cyclical movement in precipitation change among each 20-year interval. The increase in precipitation in 2021–2040 ranges from 78 to 119.1 mm, which is much larger in scale compared with the 21.3–27.9 mm precipitation change in 2041–2060. The increase in precipitation in 2061–2080 is back to the high in 2021–2040 with the increment ranges between 70.2 and 99.6 mm, which then goes back to a mild change of 39.3–54.9 mm during 2081–2100. The projections in Table 5 reveals spatial variations in the change of temperatures and precipitations. Central and northern Taiwan are projected to exhibit a larger-scale change in temperature, whereas the central and southern areas have larger precipitation changes relative to the north and the east.

Climate change impact assessment under the four scenarios are reported in Table 6. The results indicate that climate change lowers the production value of rice under all four scenarios with only three exceptions, which suggest the adverse effect of climate change on rice production. As expected, there appear to be spatial differences in terms of the negative effect of climate change on rice production. Central and southern Taiwan are projected to experience more severe loss than in other parts of the island. Under RCP6.0, the adverse effect of climate change on rice production reaches the high of approximately $2900 in the last two decades of the century.

Table 6. Impacts of selected climate change scenarios (USD per-unit farmland).

Year/Area	Rice Change in Production Value				Vegetables Change in Production Value				Fruits Change in Production Value			
	RCP2.6	RCP4.5	RCP6.0	RCP8.5	RCP2.6	RCP4.5	RCP6.0	RCP8.5	RCP2.6	RCP4.5	RCP6.0	RCP8.5
2021–2040												
North	−753	−861	−672	−1416	−56	−66	−48	−124	246	278	222	435
Central	−828	−1017	−999	−1861	−64	−84	−85	−175	266	320	311	556
South	−892	−1027	−897	−2150	−72	−86	−73	−208	282	321	283	633
East	−897	−700	−640	−1496	−73	−49	−44	−134	283	232	213	455
2041–2060												
North	−2258	−2028	−87	−543	−212	−176	33	8	674	626	83	244
Central	−2311	−2231	642	−425	−219	−200	116	21	687	680	−115	211
South	−2685	−2440	3945	−445	−262	−224	488	17	787	735	−1014	214
East	−2181	−1898	1747	−423	−205	−163	239	19	651	588	−417	208
2061–2080												
North	−2556	−2675	−932	−1350	−248	−235	−40	−45	752	821	344	518
Central	−2652	−2760	−1280	−1553	−260	−246	−79	−69	777	843	439	570
South	−2566	−2737	−1263	−1846	−251	−245	−79	−105	752	834	433	647
East	−2319	−2276	−1118	−1321	−223	−193	−63	−45	685	709	393	504
2081–2100												
North	−2788	−1992	−2299	−982	−280	−153	−169	34	807	642	751	469
Central	−2912	−2275	−2737	−793	−294	−186	−220	52	841	718	869	413
South	−2591	−2419	−2613	−1070	−281	−204	−208	18	721	755	832	484
East	−2182	−1770	−2248	−1032	−212	−131	−167	23	642	578	733	475

Note: 1 USD =30 NTD.

With a few exceptions, climate change appears to have an adverse effect on the production of vegetables, which are smaller in size compared to those for rice. There are also spatial differences in the simulated effect of climate change on vegetable production. Similar to rice, climate change impact on vegetables is larger in the northern and central areas of Taiwan. There is a gradual increase in terms of the size of the negative effect under RCP2.6 and RCP4.5. However, under RCP6.0 and RCP8.5, the effects of climate change switch in signs during the entire time span. The impact of climate change on fruits are different from the other two staple foods. The simulated results suggest that there is a gradual increase in terms of the size of the effect on the production of fruits. Except for RCP8.5, the positive impacts of climate change start with a size of around $210–$320 in 2021–2040, which later increase to approximately $640–$870 in the last two decades of the century. Under RCP8.5, the effect of climate change first increases, but then decreases in size.

The spatial differences in the simulated effect of climate change on the production of the three staple foods are similar. The increment in or loss of production is larger in the central and southern areas of Taiwan. Overall, it is found in this study that the effects of climate change exhibit spatial and seasonal variations as in previous studies, for example, [27,28]. This result is consistent with the finding in previous studies, example, [27,28]. Additionally, the present study confirms one more possible source of variations in climate change impact, namely the variations across staple food commodities.

6. Conclusions

This study provides solid evidence and a significant complement to the existing body of knowledge through the investigation of the effect of climate conditions on both crop choice and subsequent production of the three most important staple foods. According to the estimates from the structural Ricardian model, the impacts of seasonal temperature variations are found to vary significantly across the staple food commodity chosen by the farm household. Among the three staple food crops, vegetables seem to be more sensitive to the seasonal variations in temperature. The effect of seasonal precipitation variations is also found to vary significantly across the staple food commodities. Our results indicate that increasing precipitation in the winter can significantly increase the production of fruits which is heavily concentrated in southern Taiwan, whereas rice production is the most sensitive to increasing precipitation in the spring.

Assessment of the impact of climate change under four RCP scenarios suggest the adverse effect of climate change on the production of rice and vegetables. Most of the effect of climate change, however, is positive for fruits. The simulated effect of climate change under different RCP scenarios also suggest significant spatial differences in the impact of climate change on the production of the three staple foods. Central and southern Taiwan are projected to experience more severe loss in rice and vegetables production than in other parts of the island.

Possible further exploration of the present work is two-fold. First, the use of adaptation strategies other than crop choice or the use of combined coping strategies may resolve the major limitation of this study. Second, some authors, for example, [53–55], indicated that climate change impact assessment should also take the frequency and severity of extreme climatic conditions into account. A possible extension of the present study is, therefore, to explicitly acknowledge the effect of extreme weather or disaster loss in assessing the impact of climate change.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Fruits and Vegetables.

Fruits		Vegetables		
Apple	Persimmon	Amaranth	Ginger	Pea
Avocado	Pinang	Asparagus	Gracilaria	Pea seedlings
Banana	Pineapple	Asparagus bean	Green garlic	Potato
Carambola	Pitaya	Aubergine	Green onion	Pumpkin
Citrus	Plum	Bamboo shoot	Green soybean	Radish
Coconut	Plum flower	Big stem mustard	Gynura's Deux Couleurs	Spinach
Date palm	Pomelo	Bitter gourd	Kale	Sponge gourd
Grape	sweetsop	Burdock	Kohlrabi	Strawberry
Guava	Wax-jambos	Cabbage	Leaf mustard	Sweet potato leaves
Litchi		Calabash (gourd)	Leek	Taro
Loquat		Carrot	Lettuce	Tomato
Lungan		Cauliflower	Lotus root	Water bamboo

Table A1. *Cont.*

Fruits	Vegetables		
Mango	Celery	Lotus seed	Water chestnut
Olive	Celery cabbage	Melon seeds	Water nut
Other fruit	Chillies	Muskmelon	Water spinach
Papaya	Coriander	Netted melon	Watermelon
Parami	Cucumber	Onion	Winter gourd
Passion fruit	Fern	Onion bulb	Yellow daylily
Peach	Garland chrysanthemum	Oriental pickling melon	Other fruits
Pear	Garlic	Pak-Choi (Bailey)	

Table 2. Correlation coefficient of monthly temperature and precipitation.

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan	1	0.8698	0.9162	0.7584	−0.6321	0.3298	−0.155	0.0904	0.5398	0.9292	0.9111	0.9077
Feb	0.9846	1	0.9587	0.7775	−0.6569	0.3892	−0.097	0.1192	0.6651	0.8183	0.6767	0.9231
Mar	0.9039	0.9459	1	0.832	−0.6543	0.5015	−0.2304	−0.0205	0.5345	0.8501	0.7491	0.9647
Apr	0.89	0.9202	0.9444	1	−0.5808	0.5256	−0.1507	−0.2431	0.4705	0.6182	0.6002	0.8548
May	0.7752	0.8006	0.8093	0.9482	1	0.1046	−0.1262	−0.4045	−0.4363	−0.686	−0.6786	−0.5734
Jun	0.5929	0.5951	0.5663	0.761	0.9182	1	−0.5089	−0.5816	0.1048	0.1557	0.1359	0.5387
Jul	0.2225	0.2089	0.1489	0.3819	0.6366	0.8823	1	0.6763	−0.045	0.0658	−0.084	−0.2741
Aug	0.4087	0.3981	0.3413	0.5685	0.7856	0.9595	0.9735	1	0.3478	0.3115	0.1819	−0.134
Sep	0.6412	0.6581	0.6562	0.8511	0.9636	0.9501	0.7654	0.876	1	0.4863	0.374	0.5101
Oct	0.7966	0.8051	0.7917	0.9451	0.9804	0.8731	0.5801	0.7404	0.9567	1	0.9003	0.7971
Nov	0.8824	0.8935	0.8887	0.985	0.9643	0.8099	0.4645	0.6443	0.8995	0.9794	1	0.7333
Dec	0.9891	0.9901	0.9277	0.9162	0.7885	0.5701	0.173	0.3698	0.6486	0.812	0.8988	1

Note: Upper triangle reports correlation coefficient of monthly precipitation; lower triangle reports that of monthly temperature. Different highlight colors represent correlations in different seasons—grey (winter), yellow (spring), blue (summer), green (fall).

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