Efficiency of Weather Derivatives: A Study of Rice and Wheat in China

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Abstract. The efficiency of temperature-based weather derivatives (WD) in reducing risk exposure for Chinese agriculture industry is analyzed in this paper. Therefore, a put option with cumulated growing degree days as its underlying index is assumed to be bought by a farmer as a risk management instrument. A weather-yield model is constructed to find a suitable regression model to predict the crop yield based on weather variables. Through comparing the producers' revenue with and without WD for 57 years, efficiency criteria as risk measures are calculated. The study includes rice and wheat production in the area of Shanghai and Beijing. The results of the efficiency tests show that temperature-based put options are an efficient risk reducing instrument in offsetting yield shortfalls for rice and wheat in China.

1. Introduction

As an important part of the ecosystem, weather has an enormous influence on socioeconomic systems especially in the terms of agriculture, energy, transportation, construction, tourism and other sectors. Therefore, efficient weather risk management has become an urgent demand for these industries, especially to agriculture whose revenue is highly correlated to the weather factors such as temperature, rainfall, humidity and sunlight. Financial weather derivatives serve as such hedging instruments. Like any other derivatives, WD comprise futures, forwards and options in both directions as calls and puts. The underlying for WD is a weather index which is usually called heating degree days (HDD) or cooling degree days (CDD). HDD and CDD are defined as

$$HDD_n = \sum_{i=1}^{n} max\{18°\text{C} - T_i, 0\} \qquad (1),$$

$$CDD_n = \sum_{i=1}^{n} max\{T_i - 18°\text{C}, 0\} \qquad (2),$$

where $\boldsymbol{T_i}$ is the average temperature of the maximum and the minimum temperature of the day i. The base temperature of 18℃ is chosen as for the energy sector this is the usual threshold when people change from heating to cooling or vice versa (Jewson et al., 2005).

In the last decade, how to model the temperature index and how to price temperature-based WD was

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primarily studied (Alaton et al., 2002; Benth and Saltyte Benth, 2007; Schiller et al., 2012). This addresses mainly the sellers in the WD market. But for potential purchasers, the question whether WD are efficient hedging instruments is as important as pricing. However, the efficiency problem has not been analyzed sufficiently worldwide and especially not for the Chinese market in the existing literature.

Vedenov and Barnett (2004) investigated the hedging efficiency of temperature- and rainfall-based WD for corn, cotton and soybeans in the United States. Their findings indicate that WD can generally reduce the weather-related risk for farmers. However, the efficiency differs heavily between crops and districts. Further, the fitting performance of the weather-yield model has an important effect on the hedging results. Musshoff et al. (2011) studied the risk-reducing effects of rainfall options on wheat production in Northeast Germany. Based on their results, they could conclude that hedging efficiency depends on the distance between the reference weather station and the farm which is also called basis risk. When it is assumed that there is no basis risk, the hedging performance of the rainfall options was very good, while increasing the distance reduced the efficiency.

Recent studies by Turvey and Kong (2009) and Liu et al. (2010) considered China as a potential market for WD and weather-indexed insurance. Both papers stress that farmers showed interest in this kind of risk management instruments. Baojing et al. (2013) studied risk reducing effects of WD for corn production in Northeast. Their results indicate that WD are efficient hedging instruments if the fit of the model for weather-yield relationship to the data is sufficiently good. These findings are in line with the results of Vedenov and Barnett (2004) and Stoppa and Hess (2003).

At present, the Chinese financial market is a developing market and still restricted in comparison to the financial markets in the United States, Europe or Japan. This also affects the trading of WD as those financial instruments are not yet launched in China. The objective of this paper is to support with research based on Chinese data the introduction of WD as an asset class on the financial markets.

2. Empirical data

2.1 Crop selection

The two crops chosen in this paper are wheat and rice because of their comparable geographic and biological attributes. Wheat mainly grows in northern China and its seasonal distribution of growth cycle is mainly in cold season, correspondingly, rice mainly distributes in southern China and it grows in warm season. The growing season for each crop is based on its life cycle within contiguous months (Lobell and Field, 2007).

Table 1. Life cycle for wheat and rice

Wheat			Rice		
Growth phase	Reference dates	Cycle in days	Growth phase	Reference dates	Cycle in days
Seeding	15th Nov.	0	Seeding	15th Apr.	0
Emergence	1st Dec.	15	Sprout cultivation	15th May	30
Tillering	15th Dec.	45	Returning green	1st Jun.	45
Stem elongation	15th Jan.	75	Tillering	15th Jun.	60
Head emergence	15th Feb.	105	Head sprouting	1st Aug.	105
Flowering	1st Mar.	120	Milky ripe	15th Aug.	120
Maturity	1st Apr.	150	Harvest	15th Sep.	150
Harvest	15th Apr.	165			

Table 1 describes the life cycles and growth phases of wheat and rice. The growing seasons from May to October for rice and from November to April in the next year for wheat are fixed according to the life cycle table. Therefore, we can split one year into cold season (181 days) and warm season (184 days). The Figure 1 and Figure 2 show the geographical distribution of wheat and rice respectively.

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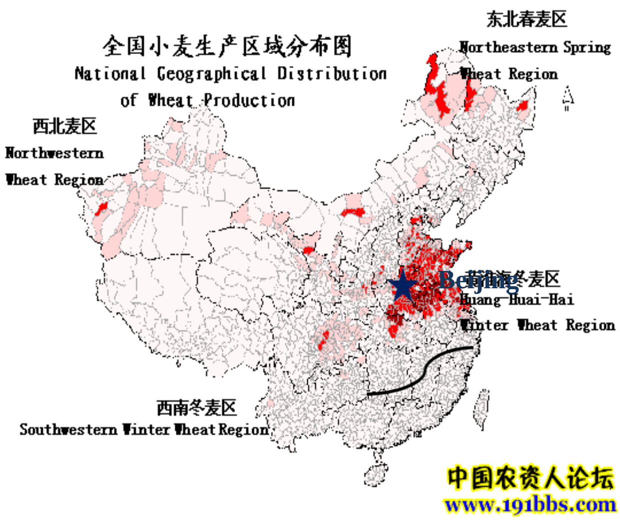
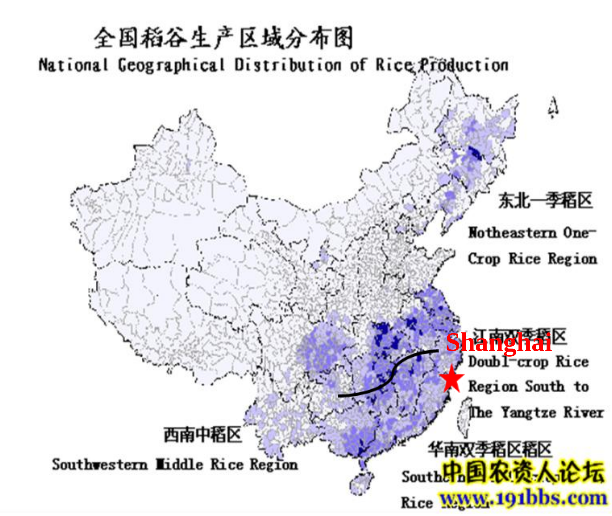
Figure 1. National geographical distribution of wheat production (left)

Figure 2. National geographical distribution of rice production (right)





2.2 Region selection

According to Stoppa and Hess (2003), if the individual production side and the place for which the WD are designed are not perfectly matched, basis risk would arise. That is to say, if the place where the weather variable is measured is different from the areas where the WD is used as a risk management instrument, the effect of weather derivatives might be distorted (Vedenov and Barnett, 2004; Musshoff et al., 2011). But it is impractical to completely eliminate the basic risk, since the advantage of lower transaction costs of WD may be offset by the additional costs if weather variables are all measured at specific weather stations and where the investors may not be interested in. Therefore, the attempt is to enlarge the spatial scale from farm level to county level where the crop yield is reported. Therefore, municipality level is chosen as the primary unit. Specifically, for each of the two crops, Beijing and Shanghai are selected as target sample cities. In total, four yield groups were selected: control city/crop groups: Beijing_Wheat, Shanghai_Rice; experimental city/crop groups: Beijing_Rice, Shanghai_Wheat.

2.3 Data collection

Yields for wheat and rice are collected from China Agriculture Data Sharing Center (CADSC) for the period from 1949 to 2007 and the temperature data are collected from China Meteorological Data Sharing Service System (CMDSSS) for the period from 1951-2010. In order to catch simultaneous data, we finally select yield and weather data for Beijing and Shanghai for a period of 57 years from 1951 to 2007.

Table 2. Descriptive statistics for crop yields of Beijing and Shanghai from 1951 to 2007

	Mean	Median	Std. Dev.	Minimum	Maximum	Number
Beijing_Wheat	208.27	200.92	126.88	26.70	394.87	57
Shanghai_Wheat	190.76	220.74	72.70	66.72	297.34	57
Beijing_Rice	333.69	351.06	109.44	95.81	527.54	57
Shanghai_Rice	380.29	349.21	105.52	210.06	551.87	57

Table 2 shows the descriptive statistics for yields, where yearly yields equal total municipality-level

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production divided by harvested acres, and the unit is kilogram per mu (kg/mu, where mu is a unit of area, 1 mu = 0.0667 hectares). As the harvest takes place only once a year, the yield data is measured yearly. The temperature data are based on daily average observations for all 57 years. Both datasets are complete. No missing or inappropriate values are detected.

3. Model for weather-yield relationship

In this section, the quantitative regression model that describes the relationship between crop yield and independent variables is developed. Schlenker and Roberts (2008) assumed that temperature has a cumulated effect on the crop yield especially during the crop's growth phase. This implies that yield growth rates should be equally affected by temperature over time. Furthermore, because improvement in agricultural technology is introduced nationally, they serve to improve crop yield in all cities. So it is plausible to think of technology progress as an omitted variable that changes over time but has equivalent effects on all cities. Thirdly, soil quality and soil type are omitted variables that are constant over time but vary across cities. Therefore, a combined time and city fixed effects regression model that describes the effect of weather variables, technology progress and soil quality on the log yield, y_{it}, in city i and year t is constructed as:

$$y_{it} = log\left(Y_{it}^{A}\right) \qquad (3),$$

$$y_{it} = \beta_0 + \beta_1 \int g(h)\Phi_{it}(h)\, dh + \beta_2 S_t + \beta_3 Z_i + u_{it} \qquad (4),$$

where Y_{it}^{A} is the actual crop yield in city i and year t, $\Phi_{it}(h)$ is the cumulated distribution function of temperature during growing season of crops in city i and year t, S_t denotes the combined effect of variables which changes over time but not over cities, which is used to capture technology progress, Z_i denotes city fixed effect which changes over city but does not change over time, such as soil quality, and u_{it}~N$(0, \sigma_{it})$ is the error term. Models based on similar assumptions are used in Schlenker and Roberts (2009), Baojing and van Kooten (2012), Baojing et al. (2013).

The heating function $g(h)$ in the model (4) is expressed as a piecewise linear function that equals to zero or the difference between temperature and the threshold. The threshold temperature $c = 4.4$°C or $c = 40$°F has been determined as an agricultural critical temperature for wheat because only if the temperature is higher than 4.4°C, wheat has enough heat to grow from one growth phase to the next and develop normally. For rice, the threshold temperature is $c = 10$°C or $c = 50$°F (Li and Zhang, 2012). It is realistic that rice's threshold temperature is higher than wheat's since rice mainly grows in warmer southern area while wheat grows in colder area with higher latitude. Hence, the heating function $g(h)$ is defined as

$$g(\mathrm{h})_{\text{wheat}} = \begin{cases} \mathrm{h} - 4.4 & \text{if h} > 4.4\text{°C} \\ 0 & \text{if h} \leq 4.4\text{°C}, \end{cases} \qquad (5)$$

$$g(h)_{\text{rice}} = \begin{cases} h - 10 & \text{if } h > 10\text{°C} \\ 0 & \text{if } h \leq 10\text{°C}\,. \end{cases} \qquad (6)$$

With a single temperature regressor and $T - 1$ binary time effected regressors, the original combined time and entity fixed effects regression model (4) has been modified as a time fixed effects regression model of the form:

$$y_{it} = \lambda_i + \beta_1 \sum_{-5}^{40} g(h + 0.5)[\Phi_{it}(h + 1) - \Phi_{it}(h)] + \delta_2 B2_t + \cdots + \delta_T BT_t + u_{it} \quad (7),$$

where the binary regressor $B2_t = 1$ if $t = 2$ and $B2_t = 0$ otherwise, and so forth. $\lambda_i, \beta_1, \delta_2, \ldots, \delta_T$ are unknown coefficients. In order to avoid perfect multicollinearity, the first binary regressor $B1_t$ has been omitted here which leads to $T - 1$ binary regressors.

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Pricing model for weather derivatives

As the weather index GDD is the most suitable underlying of WD in agriculture, the index using the heating function $g(h)$ and base temperature c from section 3 is defined as:

$$GDD_n = \sum_{i=1}^{n} max\{T_i - c, 0\} \qquad (8).$$

The strike price of the GDD put option is K which is chosen to be the long-term mean of GDD_n. The payoff of the GDD put option is defined as

$$P = \alpha\, max\{K - GDD_n, 0\} \qquad (9),$$

where for simplicity, the converting ratio α is 1 unit of currency per GDD. It is assumed that there is a constant market price of risk λ, which is assumed to be zero in this study since at present, there is no real weather derivatives market in China that could be used to calibrate λ.

According to Alaton et al. (2002), the price of the GDD put option can be obtained under the assumption that the probability that $max\{T_i - 10°\mathrm{C}, 0\} = 0$ is very low in rice growing season (May-Oct) for both Shanghai and Beijing. From the data we can see that for Shanghai_Rice the probability that the temperature is below 10°C is indeed almost zero. For the experimental group Beijing_Rice, some violations are obvious. With the assumption, the index can be rewritten as

$$GDD_{n_{rice}} = \sum_{i=1}^{n} \max\{T_i - 10, 0\} = \sum_{i=1}^{n} T_i - 10n \qquad (10),$$

where GDD_n is assumed to be normally distributed with parameters μ_n and σ_n. Hence, the pricing formula for rice GDD put option at $t \le t_1$ is given by:

$$price(t) = e^{-r(t_n - t)} \int_0^K (K - x) f_{GDD_n}(x) dx =$$

$$e^{-r(t_n-t)} \left[(K - \mu_n) \left(\Phi\left(\frac{K - \mu_n}{\sigma_n} \right) - \Phi\left(-\frac{\mu_n}{\sigma_n} \right) \right) + \frac{\sigma_n}{\sqrt{2\pi}} \left(e^{-\frac{(K-\mu_n)^2}{2\sigma_n^2}} - e^{-\frac{\mu_n^2}{2\sigma_n^2}} \right) \right] \qquad (11),$$

where r denotes the risk-free interest rate and Φ is the cumulated distribution function of the standard normal distribution. The contract duration is from t to t_n.

More problems arise for wheat because the probability of $max\{T_i - 4.4°\mathrm{C}, 0\} = 0$ is not always equal to zero in wheat's cold growing season. In the data, it can be found that temperatures exist that are close or lower than the threshold temperature during the growing season. An approach to avoid the assumption of Alaton et al. (2002) is to apply Monte Carlo simulation instead or additionally.

4. Efficiency analysis

For the efficiency analysis, it is assumed that only growing degree days based put options are bought by crop producers who produce one type of crop in Beijing or Shanghai. According to Vedenov and Barnett (2004), we analyze the performance of WD in protecting farmers' income by comparing their production revenues with and without options:

$$R_t = pY_t^{det}, t = 1, \dots, T \qquad (12),$$

$$R_t^{'} = pY_t^{det} + payoff\ of\ option - price\ of\ option, t = 1, \dots, T \qquad (13),$$

where Y_t^{det} represents the de-trended crop yield, which is derived from the predicted yield $\widehat{Y}_t$ or historical yield Y_t^A after a de-trending process. Using the weather-yield model (7), the log crop yield $\widehat{y}_t$ can be predicted from temperature data. However, the predicted yield $\widehat{Y}_t$ and the historical

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yield Y_t^A still contain the trend yield Y^T, because, in most regions, the production yield has a significant positive autocorrelation with time mainly due to the technology progress. Therefore, a process to separate the technology influence on yield is needed to identify the weather's contribution to yields variability directly from the original yield data.

Further, we assume that the crop price p is constant over time. The price for wheat and rice are reported on the official website of Ministry of Agriculture of the People's Republic of China (MAPRC). The November average rice price per kilogram on the December contract in 2007 is 3.03 RMB per kilogram and the November average wheat price per kilogram on the December contract in 2007 is 1.62 RMB per kilogram. This method is consistent with the assumptions in the literature (Vedenov and Barnett, 2004; Musshoff et al., 2011).

The total yield and weather time series from 1951 to 2007 is divided into two subsets: the in-sample subset contains the predicted values from 1951 to 1978 (28 years) and the second out-of-sample subset contains the forecasted values from 1979 to 2007 (29 years). The in-sample subset is used to estimate the parameters of the regression model (7). In contrast, the forecast using the out-of-sample subset is constructed for efficiency tests of WD. Three test criteria are implemented to test whether the risk exposure could be reduced if producers buy GDD put options - the root mean square loss (RMSL), value-at-risk (VaR), and certainty-equivalent revenues (CERs) (Vedenov and Barnett, 2004).

Root mean square loss (RMSL) is a measure to estimate the loss derived from the root mean squared error (RMSE) in statistics. RMSL is a risk function that quantifies the difference between actual revenue and the expected value. RMSL measures the root average of the squares of the loss. The loss is the maximum amount between zero and the loss compared with the expected revenue, such that

$$RMSL = \sqrt{\frac{1}{T}\sum_{t=1}^{T}[max\,(p\bar{Y} - R_t, 0)]^2} \qquad (14).$$

Value-at-risk (VaR) is defined as, given a confidence level $\alpha \in (0,1)$, the VaR of a loss X or its distribution function $F(x) = P(X \leq x)$ at the confidence level α, denoted by VaR_α is defined as

$$VaR_\alpha(X) = in\,f\{x \in R\text{: } \mathrm{P}(X > x) \leq 1 - \alpha\} \qquad (15).$$

In our case, for a distribution function of revenue R, the probability that the revenue of crops is smaller than the critical value VaR is α:

$$\mathrm{P}\{R < VaR_\alpha\} = \alpha \qquad (16).$$

The empirical distributions of R with and without the options are used to calculate $VaR_{0.05}, VaR_{0.10}, VaR_{0.20}$ for both in-sample and out-of-sample periods.

Certainty-equivalent revenues (CERs) is another measure that considers a pre-specified risk premium θ to express revenues. Risk premium θ is used by risk-averters to eliminate the uncertainty in revenue by sacrificing θ% of the expected revenue. To obtain the CERs, we start with a negative exponential utility function, which is expressed as:

$$U(R) = 1 - ex\,p(-\gamma R) \qquad (17).$$

The expected utility function can be expressed as a utility function of certain expected revenue (after eliminate the risk premium θ). We determine the risk premium θ at 5%, 10% and 20% level respectively, then certainty-equivalent revenues are calculated from the condition $U(CER) = E_R[U(R)]$ (Vedenov and Barnett, 2004).

5. Results and implications

Using OLS regression, the estimation results of the coefficients in the model (7) and relevant inferences are listed in Table 3. Note, t-statistics are given in parentheses under the coefficients and adjusted R squares are given in the last row. Each coefficient is statistically significant at the *5% or **1% significance level.

Table 3. Regression analysis of the effect of temperature on crop yield

Dependent variable: log yield $\boldsymbol{y_{it}}$					
Regressor	coefficient	Beijing_Wheat	Beijing_Rice	Shanghai_Wheat	Shanghai_Rice
Intercept	λ_i	1.23 (6.28**)	1.09 (3.40**)	2.52 (34.92**)	2.46 (32.91**)
Cumulated weather effects	β_1	0.0024 (5.06**)	0.000663 (4.36**)	-0.00012 (-1.72*)	0.00011 (3.44**)
Time effects	δ_t	yes	yes	Yes	yes
Adjusted R square	$\bar{R}^2$	60.55%	54.35%	40.87%	70.36%

According to Table 3, β_1 are significantly positive in Beijing_Wheat, Beijing_Rice and Shanghai_Rice. This means that increasing growing degree days increase crop yield which is as expected for the control groups, Beijing_Wheat and Shanghai_Rice. For Shanghai_Wheat, this coefficient is negative which can help to explain why this climatic zone is naturally not the best region for wheat. As the residuals of the regression have a very similar size, it is assumed that heteroscedasticity is not present to that extent that it could interfere with regression results.

For the numerical results of GDD put options for the four groups, the option duration is set to half a year and the expiry date is set on the last day of October for rice and on the last day of April for wheat. We assume that the annual risk-free interest rate r is 2.5%. The strike levels were calculated by the long-term mean of growing degree days for crop's growing seasons.

Table 4. GDD put options (year 1991) pricing with Monte Carlo simulation and Alaton et al's formula (2002)

	Option payoff (RMB) $\boldsymbol{P}$	Strike price (GDD) $\boldsymbol{K}$	Option price (RMB) - Monte Carlo simulation	Option price (RMB) -Alaton et al's formula (2002)
Beijing_Wheat	112	410	37.53	34.46
Beijing_Rice	144	2130	57.02	59.36
Shanghai_Wheat	158	1010	45.78	46.30
Shanghai_Rice	184	2650	48.73	49.88

Table 4 reports numerical results of the pricing model for the year 1991 as an example. The second column lists the option payoffs according to the strike levels in the third column. The fourth and fifth columns report the simulated option prices using Monte Carlo simulation and Alaton et al.'s formula (2002).

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The efficiency test for GDD put options based on RMSL (Table 5) demonstrates that WD perform well in risk reducing both on revenue of wheat and rice no matter whether in Beijing or Shanghai. GDD put options show a relatively higher effect on Shanghai's crops than on crops in Beijing in- and out-of-sample. Secondly, the effect of the options for both Beijing and Shanghai wheat is higher than for rice. A reasonable explanation could be that winter growing wheat is more sensitive to the change of temperature than rice, therefore temperature-based WD show a better performance in risk reducing. The results obtained in this study support the use of WD more than the results of Vedenov and Barnett (2004).

Table 5. Efficiency of GDD put option measured by root mean square loss (RMSL)

	In-Sample (1951-1978)			Out-of-Sample (1979-2007)		
City/Crop	Without Option (RMB/mu)	With Option (RMB/mu)	Percent Change	Without Option (RMB/mu)	With Option (RMB/mu)	Percent Change
Beijing_Wheat	52.83	47.52	-10.05%	91.48	86.68	-5.25%
Shanghai_Wheat	48.93	40.35	-17.54%	29.89	24.56	-17.83%
Beijing_Rice	192.00	173.14	-9.82%	129.30	126.19	-2.41%
Shanghai_Rice	101.40	87.16	-14.04%	193.72	176.37	-8.96%
Note: Negative (positive) change in RMSL is consistent with lower (higher) risk exposure.						

Taking the criteria of VaR (Table 6) and CER (Table 7) into account, similar results are obtained as for RMSL. Generally, all GDD put options reduced the risk exposure for all four crop/city groups both in- and out-of-sample at different VaR levels and risk-aversion levels. Very few exceptions were found (three out of 24 for VaR, two out of 24 for CERs). Again, the results of Vedenov and Barnett (2004) are similar. However, they reported more cases in which the options could not reduce risk using either VaR or CERs as risk measures.

Table 6. Efficiency of GDD put option measured by value-at-risk (VaR)

	In-Sample (1951-1978)			Out-of-Sample (1979-2007)		
City/Crop	Without Option (RMB/mu)	With Option (RMB/mu)	Change (RMB/mu)	Without Option (RMB/mu)	With Option (RMB/mu)	Change (RMB/mu)
	$\boldsymbol{VaR_{0.05}}$					
Beijing_Wheat	249.79	270.91	21.12	258.03	280.75	22.72
Shanghai_Wheat	317.88	332.15	14.27	324.11	343.39	19.28
Beijing_Rice	891.75	921.49	29.74	834.93	893.51	58.68
Shanghai_Rice	845.38	887.23	41.85	851.49	912.73	61.24
	$\boldsymbol{VaR_{0.10}}$					
Beijing_Wheat	260.59	256.34	(4.25)	306.17	323.57	17.40
Shanghai_Wheat	323.12	330.32	7.20	342.74	360.40	17.66

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Beijing_Rice	929.45	971.69	42.24	1037.51	995.36	(42.15)
Shanghai_Rice	883.45	930.66	47.21	971.97	1012.46	40.49
	$VaR_{0.20}$					
Beijing_Wheat	279.66	290.23	10.57	387.96	405.05	17.09
Shanghai_Wheat	336.13	340.24	4.11	365.33	367.78	2.45
Beijing_Rice	1052.19	1095.39	43.20	1158.04	1108.67	(59.37)
Shanghai_Rice	951.18	1011.33	60.15	1159.41	1191.62	32.21
Note: Higher (lower) VaR corresponds to lower (higher) risk exposure.						

Table 7. Efficiency of GDD put option measured by certainty-equivalent revenues (CERs)

	In-Sample (1951-1978)			Out-of-Sample (1979-2007)		
District/Crop	Without Qption (RMB/kg)	With Option (RMB/kg)	Change (RMB/kg)	Without Option (RMB/kg)	With Option (RMB/kg)	Change (RMB/kg)
	Risk Premium θ=0%					
Beijing_Wheat	358.00	380.36	22.36	510.60	492.73	(17.87)
Shanghai_Wheat	409.72	414.37	14.65	404.91	420.40	15.49
Beijing_Rice	952.67	1007.03	54.36	1260.56	1279.93	19.37
Shanghai_Rice	1098.07	1240.21	142.14	1397.69	1481.08	83.39
	Risk Premium θ=5%					
Beijing_Wheat	340.10	361.34	21.24	485.07	478.09	(6.98)
Shanghai_Wheat	389.23	413.65	24.42	384.66	409.88	25.22
Beijing_Rice	905.04	936.68	31.64	1197.53	1215.93	18.40
Shanghai_Rice	1043.17	1183.20	140.03	1327.81	1502.03	174.22
	Risk Premium θ=10%					
Beijing_Wheat	322.20	342.32	20.12	459.54	463.46	6.08
Shanghai_Wheat	368.75	392.93	24.18	364.42	389.36	24.94
Beijing_Rice	857.40	906.33	48.92	1134.50	1151.94	17.43
Shanghai_Rice	988.26	1026.19	37.93	1257.92	1422.97	165.05

6. Conclusion and limitations

The weather-yield model (7) showed a high prediction power in forecasting crop yield from temperature variables. Compared with the literature, this performance is at the higher end of the reported ranges. We calculated payoffs and prices of temperature-based put options using Alaton et al.'s pricing model (2002) and Monte Carlo simulation. Finally, the farmer's crop revenue with and without WD was obtained to conduct the efficiency analysis with three criteria (RMSL, VaR, CERs).

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According to this we can summarize that the results of the efficiency tests showed that temperature-based options are overall an efficient instrument in reducing weather risk. The findings in this study support the launch of WD in China. More detailed, WD seem to perform better in warm areas than in cold areas, because crops in warm areas are more sensitive to freezing days. The translation between high predicting power of the weather-yield model and high protection power of WD is still not obvious.

Potential limitations in constructing both the weather-yield model and pricing model might result to unexpected consequences or bias in the efficiency analysis. Possible problems are listed as plausible direction for further research.

Firstly, the de-trending procedure to divide the yield into results based on agricultural technology progress or based on weather factors could be improved. The crop yield as a time varying function which is disassembled into a drift and a volatility part could be regarded. Secondly, the yield change cannot be attributed to a single weather factor. Choosing proper weather variables for the model is necessary to find the real relationship between weather and yield. Thirdly, climate change has different effects in different areas. This is not only due to the regional climate characteristic but also depends on human activities such as management measures and adaptation measures on climate change. Further, the WD pricing model of Alaton et al. (2002) assumes that the volatility is monthly constant. Models that allow a daily deterministic volatility like the CAR model of Benth and Saltyte Benth (2007) or even models with stochastic volatility should be considered to minimize errors for temperature modeling. Finally, the contract period of the GDD put option is with six months relatively long, because the collected yield data are at annual level. However, the cumulated growing degree days during this long period might hide unusual variance in different months. Further research should focus on filtering and selecting dominant meteorological elements and key growth month for the crop to design options with shorter contract periods.

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