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New Weather Indices for China: Tool of Risk Control of International Supply Chain

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Abstract: China is at the core of the world's supply chain because of its focus on production and consumption. However, as weather can significantly affect supply chain operations, China plans to introduce weather derivatives to secure the multinational supply chain. Using historical records over the decade, weather derivatives could be an important tool for hedging risk and meeting the needs of Chinese market. In this paper, new weather indices for China financial markets are experimentally created through simulated machine learning to assess the ability of the weather indices to reduce risk. Through a simulation test from 2008 to 2017, the indices were found to successfully match 98% of the risk with the situation across two dimensions: *i)*. changing Chinese weather data; and *ii)*. a connection with US weather indices.

Keywords: ANNs, C-CDDs, DCC-GARCH model, weather derivatives

1. INTRODUCTION

While weather is generally predictable, its effects are often random. Therefore, the weather plays a significant role in production, especially for the energy industry [1] and other industries greatly affected by weather changes. Studies have shown that weather risks directly led to losses of around $1 trillion in the US economy [2, 3]. Many enterprises also face dramatic changes in sales volumes because of weather variations, which can significantly affect viability and even hinder industrial development [4, 5].

As risk management is a vital part of every enterprise [6], it was inevitable that weather derivatives would become a trend. *Su (2010)* [7] stated that weather derivatives could be used to hedge the risk of extreme or prolonged weather conditions [8]. The first weather derivatives appeared in the US in 1997, and in 1998, the UK, Germany, Belgium, and Norway also introduced weather derivatives to hedge the risk of weather damage. In 1997, the trading volume was $500 million, which rose to $1 billion in 1998 and to $3 billion in 1999, proving their viability in financial markets.

In the early years, weather derivatives were only traded in US over-the-counter (OTC) markets. However, in January, 2000, the London International Financial Futures Exchange (LIFFE) in England began to trade these derivatives online [9]. Exchange markets now include exchanges such as the Chicago Merchandise Exchange (CME) and the International Exchange in Atlanta. The types of weather derivative futures and options available include Cooling Degree Days (CDDs), Heating Degree Days (HDDs), and Cumulative Average Temperatures (CATs), with many corporations choosing to hedge risk for the best results.

Currently, the US, the UK, Japan, Australia, and some cities in Europe have introduced and are trading weather derivatives; however, China has not yet built a standardized weather derivatives trading platform. As China is at the core of the global supply chain, adverse weather conditions inevitably influence the development of the global economy; therefore, the risks caused brought by adverse weather need to be well-managed to ensure a stable global supply chain and reduce the negative influences. China also has a large well developed

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agricultural sector [10] that contributes significantly to GDP every year; however, production can be easily influenced by adverse weather and climate change [11]. Therefore, the introduction of weather derivatives is vital for securing the global supply chain and developing the domestic economy. If an enterprise chooses to purchase Chinese weather derivatives, they could better hedge their risks and maintain profitability, which would be beneficial to the development of the global economy and the international financial markets. Weather derivatives allow for the risks associated with the energy industry and agriculture to be well managed, and can and ensure the global supply chain and international financial market stability.

Although China has not launched weather derivatives on the financial markets, there has been some associated weather derivative research. For example, *Hong et. al (2013)* [9] proposed a method using peer group analysis to set a prior price for new weather derivatives, and *Zong et. al (2016)* [12] proposed regional weather indices for China and demonstrated that weather derivatives were a practicable tool for efficiently hedging risk. Weather derivatives are fundamentally dependent on temperatures; according to data from the Chinese Government Network (2014), the 665 cities in mainland China had contract difficulties because of difficulties in obtaining temperature data [12].

As contract prices are based on monthly and quarterly cumulative weather indices, the fluctuations in the weather indices are very important. Therefore, in this article, more attention is paid to the design of Chinese weather indices and new feasible and stable Chinese weather indices proposed. Being different with the weather indices of other cities, the new weather indices we propose is not only decided by local weather but influenced by global weather derivatives market. Therefore, the new weather indices will have much more possibility to suit the global market and improve its viability and adaptation.

In this article, new weather indices for Chinese weather are proposed using a DCC-GARCH model and ANNs. In Section 2, the models used are introduced, in Section 3 the city selection process is described, and a new equation for the weather indices proposed. A simulation and discussion are presented in Section 4, and the conclusion is given in Section 5.

2. METHODOLOGY

2.1 Dynamic conditional correlations - Generalized autoregressive conditional heteroscedasticity

The dynamic conditional correlation-Generalized autoregressive conditional heteroscedasticity (DCC-GARCH) model is based on the Generalized autoregressive conditional heteroscedasticity (GARCH) model proposed by *Bollerslevb (1986)* [13] and the generalized ARCH model by *Engle (1982)* [14]. The GARCH(p, q) model is described as follows:

$$\varepsilon_{\mathrm{t}} = \sigma_t z_t \tag{1}$$

$$\sigma_{\mathrm{t}}^2 = a_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \tag{2}$$

where z_t represents the uniform and independent random variables, and σ_t denotes the conditional variances. The parameter p and q represent the order for the ARCH and GARCH models; when $p = 0$, it is considered an ARCH(q) model.

Weather derivatives are monthly or quarterly contracts based on an index [4]. As Chinese financial markets have been gradually integrated into the global financial system [15], and it is hoped that these new weather indices can be integrated into international weather derivatives markets, the new weather indices need to be correlated tightly with weather indices in other cities to ensure stability and feasibility. However, because the GARCH model was unable to represent the co-movement of two indices, we can hardly make a connection between Chinese market and global markets. Therefore, in this article, we choose the DCC-GARCH model to calculate the dynamic conditional coefficients to make a tightly connection with markets trading weather derivatives and make sure the viability and adaptation of the new weather indices we proposed. In 2002, *Engle (2002)* [16] proposed the Dynamic conditional correlation-Generalized autoregressive conditional heteroscedasticity (DCC-GARCH) model to calculate the co-movement of two markets. In Engle's model:

$$H_{\mathrm{t}} = D_t R_t D_t \tag{3}$$

where R_t is a $n \times n$ correlation matrix.

$$D_t = diag\{\sqrt{h_{ii,t}}\} \qquad i = 1,\ 2,\ .n \tag{4}$$

and

$$h_{ii,t} = \alpha_{i0} + \alpha_{i1}\varepsilon_{i,t-1}^2 + \alpha_{i2}J_{i,t-1}\varepsilon_{i,t-1}^2 + \beta_{i1}h_{ii,t-1} \tag{5}$$

where $J_{i,t-1} = 1$ if $\varepsilon_{i,t-1} < 0$, else $J_{i,t-1} = 0$.

$$Q_t = (1-a-b)S + au_{t-1}u_{t-1}^{'} + bQ_{t-1} \tag{6}$$

where $u_t = \varepsilon_t / D_t$, the conditional correlation matrix of ε_t is derived from $R_t = E(u_t u_t' | I_{t-1})$, and S is a matrix of the location parameters. Another conditional correlation matrix R_t can be defined as

$$R_t = diag(\sqrt{q_{11,\mathrm{t}},...,q_{\mathrm{nn,t}}})Q_t diag(\sqrt{q_{11,\mathrm{t}},...,q_{\mathrm{nn,t}}}) \tag{7}$$

The elements of R_t can be expressed as

$$\rho_{ij,t} = q_{ij,t}\sqrt{q_{ii,t}q_{jj,t}} \tag{8}$$

which equals

$$\rho_{ij,t} = [(1-a-b)\overline{q_{ij}} + bq_{ij,t-1} + au_{i,t-1}u_{j,t-1}] \times \sqrt{[(1-a-b)\overline{q_{ii}} + bq_{ii,t-1} + au_{i,t-1}^2][(1-a-b)\overline{q_{jj}} + bq_{\mathrm{jj},t-1} + au_{j,t-1}^2]} \tag{9}$$

The dynamic correlation coefficients are nonlinear functions of the two parameters *a* and *b* from the DCC model [17]. In this article, the DCC-GARCH model is used to estimate the volatility of data and ensure the co-movement of the new weather indices with existing weather indices, in order to improve the feasibility and stability of the proposed weather indices.

2.2 Artificial neural networks(ANNs)

During data classification and prediction, ANNs simulate the learning processes of human brains [18] and are composed of three parts; an input layer, hidden layers, and an output layer. Each neuron has an activate function, with variables distributed to different neurons in the hidden layers based on different weights. The ANNs structure is shown in Figure 1.

The ANN is a nonlinear model that can efficiently learn data characteristics and encapsulate time dependency [19]. As weather contract prices are based on monthly or quarterly cumulative indices, the contract price can be set based on the proposed weather derivatives; therefore, the feasibility and stability of the weather indices are very important when introducing weather derivatives and developing weather indices. In recent years, there have been some methods proposed to research and predict weather derivative indices. *Zapranis et. al(2009)* [19] proposed a model that demonstrated that neural networks were better able to approximate any nonlinear process. Therefore, based on the characteristics of the weather derivatives indices, ANNs were selected to simulate the proposed indices. Using machine learning, the stability and feasibility of the new weather indices were tested, the details of which are in Section 4.

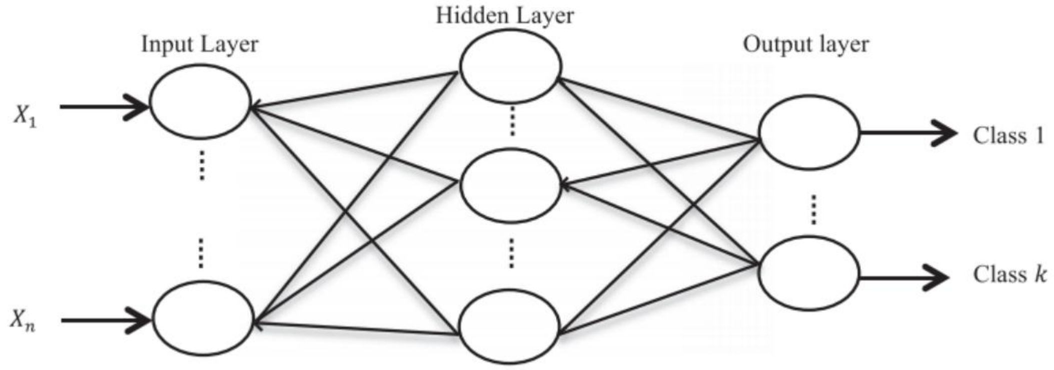

Figure 1. A three-layered artificial neural network

3. DATA SELECTION AND MODELING

3.1 Data selection

3.1.1 Selection of Chinese cities

As the new Chinese weather indices were developed based on existing CDDs, they could be the basis for the Chinese weather derivative development. Because of China's size, it is not possible to have weather derivatives for the whole country; therefore, it is necessary to develop regional Chinese weather indices. There are four dominant futures trading markets in China; Dalian, Shanghai, Shenzhen and Zhengzhou, of which Shanghai is the most important as it is the economic and financial center of China and an important harbor trading city. Therefore, Shanghai and its surrounding area were set as the research region for the design of the new weather indices for four main reasons. *i)*. Shanghai is the economic and financial center of China, with a GDP of 2.5 trillion RMB in 2015 *(from: http://data.stats.gov.cn/index.htm)*, and the cities near Shanghai such as Hangzhou and Nanjing also contribute around 1 trillion RMB GDP each year. This region that encompasses Shanghai, Jiangsu province and Zhejiang province contributes approximately 16.6% to Chinese GDP *(from: http://data.stats.gov.cn/index.htm)*. *ii)* Shanghai and its surrounding areas annually face adverse weather and regularly suffer from typhoon and flood damage, which can result in enormous losses, especially for energy enterprises. *iii)* The weather conditions in Shanghai and its surrounding cities are generally stable, which is beneficial for derivatives trading.

Therefore, Shanghai was chosen as the center for the proposed weather derivatives, with the cities surrounding Shanghai selected for the regional temperatures. Therefore, three cities; Shanghai, Hangzhou and Nanjing; were selected for the regional temperatures. The correlation coefficients for the monthly average temperatures over 25 years for Shanghai, Nanjing and Hangzhou were 1, 0.994, 0.995, respectively, indicating a tight correlation between the three cities.

3.1.2 Selection of cities to trade weather derivatives

There are 24 cities in the US, 11 cities in Europe, 6 cities in Canada, 3 cities in Australia, and 3 cities in Japan trading weather contracts. As Australia is located in the southern hemisphere and has different weather conditions to China, geographic conditions in Australia were not considered. The geographic conditions of all other cities except Australia are shown in Table 1. As can be seen, there are similar geographic conditions in China and the US, and they both also have large land masses and similar latitudes. Further, because of the number of cities trading weather derivatives in the US, the weather derivatives market is mature; therefore, our research was combined with the US weather indices. The main US weather indices are HDDs, which trade from November to April, and CDDs, which trade from April to October. In this article, CDDs were chosen as the basic weather indices, primarily because HDDs can be retrieved from the CDDs [20]. CDDs are calculated from the daily average temperatures, the calculation method for which is as follows:

$$CDDs = \sum_{t=T_1}^{T_2} \max[W_t - 18^{\circ}\mathrm{C}, 0] \tag{10}$$

where T_1 and T_2 denote the beginning and the end of a month or a season, and W_t represents the average value of the maximum and minimum temperatures of the day; therefore, there is a tight correlation between the average temperature values and the CDDs values.

Table 1. Latitude and longitude of main cities

Country	City	Coordinate	City	Coordinate	City	Coordinate
US	Atlanta	33 °46'N, 84°25'W	Detroit	42 °23'N, 83 °05'W	New York	40 °44'N, 73 °55'W
	Baltimore	39 °17'N, 76 °37'W	Houston	29 °45'N, 95 °23'W	Philadelphia	40 °N, 75 °09'W
	Boston	42 °19'N, 71 °05'W	Jacksonvile	30 °2'N, 81 °4'W	Portland	45 °31'N, 122 °39'W
	Chicago	41 °53'N, 87°37'W	Kansas	39 °02'N, 94 °33'W	Raleigh	35 °47'N, 78 °39'W
	Cincinnati	39 °1'N, 84 °3'W	Las Vegas	36 °1'N, 115 °1'W	Sacramento	38 °34'N, 121 °28'W
	Colorado Springs	38 °51'N, 104 °47'W	Little Rock	34 °44'N, 92 °19'W	Salt Lake City	40 °46'N, 111 °52'W
	Dallas	32 °47'N, 96 °47'W	Los Angeles	34 °05'N, 118 °22'W	Tucson	32 °13'N, 110 °58'W
	Des Moines	41 °36'N, 93 °38'W	Minneapolis	0 °45'N, 93 °15'W	Washington	38 °53'N, 77 °02'W
Europe	Amsterdam	52 °21'N, 4 °52'E	Barcelona	41 °18'N, 2 °06'E	Berlin	52 °31'N, 13 °2'E
	Essen	51 °27'N, 7 °00'E	London	51 °3'N, 0 °07'E	Madrid	40 °26'N, 3 °42'E
	Oslo	59 °56'N, 10 °41'E	Paris	48 °51'N, 2 °2'E	Prague	50 °05'N, 14 °25'E
	Rome	41 °52'N, 12 °37'E	Stockholm	59 °23'N, 18 °00'E		
Japan	Hiroshima	34 °23'N, 132 °27'E	Osaka	34 °4'N, 135 °30'E	Tokyo	35 °41'N, 139 °44'E
Canada	Calgary	51 °05'N, 114 °05'W	Edmonton	53 °34'N, 113 °25'W	Montreal	45 °3'N, 73 °35'W
	Toronto	43 °4'N, 79 °22'W	Vancouver	49 °13'N, 123 °06'W	Winnipeg	49 °53'N, 97 °1'W
China	Beijing	39 °55'N,116 °23'E	Changchun	43 °5'N,125 °2'E	Changsha	28 °1'N,113 °E
	Chengdu	30 °37'N,104 °06'E	Chongqing	29 °31'N,106 °35'E	Foochow	26 °01'N,119 °2'E
	Guangzhou	23 °10'N，113 °18'E	Guiyang	26 °35'N,106 °4'E	Haikou	20 °03'N,110 °10'E
	Hangzhou	30 °1'N,120 °07'E	Harbin	45 °45'N,126 °41'E	Hefei	31 °51'N,117 °16'E
	Huhehot	40 °48'N，111 °38'E	Hong Kong	22 °17'N,114 °08'E	Jinan	36 °5'N,117 °E
	Kunming	25 °04'N,102 °41'E	Lanzhou	36 °01'N,103 °45'E	Lhasa	29 °41'N,91 °1'E
	Macao	22 °11'N,113 °33'E	Nanchang	28 °38'N,115 °56'E	Nanjing	32 °03'N,118 °46' E
	Nanning	23 °N,108 °E	Shanghai	31 °14'N,121 °27'E	Shenyang	41°48′N,123°25′E
	Shijiazhuang	38 °04'N,114 °28'E	Taipei	25 °02'N,121 °38'E	Taiyuan	37 °5'N,112 °3'E
	Tianjin	39 °08'N,117 °12'E	Urumchi	30 °35'N,114 °19'E	Xining	36°34′N,101°49′E
	Xian	34 °16'N,108 °54'E	Wuhan	30 °35'N,114 °19'E	Yinchuan	38 °28'N ,106 °13'E
	Zhengzhou	34 °35'N,113 °38'E				

Two American cities were chosen that had high daily average temperature correlation coefficients with Shanghai. Therefore, the new weather indices included two parts: regional China and part of the existing US weather indices. The correlation coefficients were calculated for the monthly average temperatures in US cities and Shanghai. The final American cities chosen were Las Vegas and Little Rock as these two cities were found have high monthly average temperature correlation coefficients of 0.9122 and 0.9054.

3.2 Weather indices modeling

In this article, new weather indices are proposed to introduce Chinese weather derivatives. As China is the third largest country in the world and has 665 cities, it would be difficult for Chinese financial markets to introduce weather derivatives for only one city. Therefore, it was decided that the best way to introduce weather derivatives was to select a part of regional China and consider the weather conditions in several vital cities [11]. In this way, the scope of application for the proposed weather derivatives was broadened. Therefore, a representative city was chosen as the central city and two more cities near the center city were chosen as the regional cities. To ensure a tight correlation with the existing weather derivatives markets, the influence of international markets was also considered, with the two cities with the highest weather condition correlation coefficients with the center cities being chosen. Therefore, the proposed weather index was included a regional section and an existing sections. The equations for the new Chinese Cooling Degree Days indices(C-CDDs) were as follows:

$$C-CDDs=kCDDs_{regional}+(1-k)CDDs_{exsited} \tag{11}$$

$$CDDs_{regional}=\sum_{i=1}^{I}\max(\alpha_i T_i-18^{\circ}\mathrm{C},0) \tag{12}$$

$$CDDs_{exsited}=\sum_{j=1}^{J}\beta_j CDD_j \tag{13}$$

where i denoted the Chinese cities Hangzhou, Nanjing and Shanghai, and j represented the cities which already had weather derivatives; Las Vegas and Little Rock; and k, α_i and β_j were all parameters. Therefore, the equations above were used to develop the new weather indices. The calculation coefficients α_i and β_j for the regional temperatures were defined by:

$$\alpha_{\mathrm{i}}=\frac{\alpha_i}{\sum_{i=1}^{3}\alpha_i} \tag{14}$$

where i represented the researched cities, α_i denoted the correlation coefficients between city i and Shanghai, and the number 3 indicated Shanghai, Hangzhou, and Nanjing. The same method was used to calculate the coefficients β for the international CDDs. The coefficients were compared, Las Vegas and Little Rock selected, and the β value calculated using a similar method.

4. PARAMETER SETTLEMENT AND DISCUSSION

4. 1 Parameter settlement

Two principles were followed to develop the proposed weather derivatives; *i.*) to connect the Chinese weather derivatives indices with the US weather derivative indices to ensure feasibility of the new Chinese weather indices and to ensure that there were highly dynamic correlation coefficients between the Chinese weather indices and US city weather indices using the DCC-GARCH model; and *ii)* as these weather indices described the Chinese weather condition, the domestic section needed improving, which required the k value in equation (11) to be improved.

For this research, 10 years of daily average temperatures from April to October were collected for each of cities chosen; Shanghai, Nanjing, Hangzhou as the Chinese cities, and Las Vegas and Little Rock, which had existing weather indices. The DCC-GARCH (*1,1*) model was used to simulate the CDDs for the Chinese cities and for the existing weather indices. As the daily average temperatures in Las Vegas were found to have the highest linear correlations with Shanghai, Las Vegas was selected as the matching city to analyze the DCC between C-CDDs and CDDs in Las Vegas (CDDs-LV) to set parameter *k*.

The data characteristics were then set, including the C-CDDs for different k values and the CDDs-LV. The characteristics for these data were found to be similar. As the ADF test found the data to be non-stationary, the 1^{st} difference data was set as the data to be analyzed for the building of the DCC-GARCH model. The ADF test indicated that the 1^{st} difference data was stationary and that the data for each year was almost normal with weekly skewness and kurtosis, and the McLeod Li test showed a significant ARCH effect. Based on these characteristics, the DCC-GARCH model was built to calculate the dynamic conditional correlation coefficients. The DCC (*1, 1*) and the GARCH (*1, 1*) model were both chosen.

It was found that the DCC data fluctuated around an approximate certain number. Therefore, the mean DCC value was calculated as the DCC for each year, the results for which are shown in Table 2.

Table 2. DCC for the different k values in ten years

DCC (mean value)	k value (0 - 1 pause: 0.1)										
	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
2008	0.72	0.72	0.72	0.71	0.71	0.69	0.66	0.61	0.47	0.27	0.01
2009	0.73	0.73	0.73	0.73	0.71	0.68	0.65	0.58	0.47	0.28	0.04
2010	0.62	0.62	0.62	0.62	0.61	0.60	0.56	0.49	0.37	0.22	0.06
2011	0.57	0.56	0.56	0.55	0.54	0.53	0.48	0.42	0.33	0.21	0.04
2012	0.64	0.65	0.65	0.65	0.64	0.63	0.61	0.55	0.45	0.28	0.09
2013	0.69	0.69	0.69	0.69	0.69	0.68	0.66	0.62	0.51	0.28	-0.02
2014	0.73	0.73	0.73	0.73	0.72	0.70	0.67	0.60	0.47	0.22	-0.10
2015	0.71	0.71	0.71	0.70	0.69	0.67	0.64	0.57	0.46	0.26	0.07
2016	0.73	0.74	0.73	0.73	0.72	0.70	0.64	0.58	0.47	0.30	0.07
2017	0.70	0.70	0.70	0.69	0.67	0.64	0.59	0.50	0.36	0.19	0.07
Mean	0.685	0.684	0.683	0.679	0.670	0.651	0.615	0.553	0.434	0.249	0.033

From Table 2, as *k* was below 5, this was unable to show the influence of the changes in Chinese temperature, with a k above 0.7 showing a poor dynamic correlation with the US weather indices. Therefore, k = 0.6 was set as a suitable value for the proposed principles. To gain a more accurate *k* value, a further calculation was conducted. Therefore, a *k* value around from 0.55 to 0.65 was assumed to calculate the DCC value, the results for which are shown in Table 3.

Table 3. DCC for different k values in ten years

DCC (mean value)	k value (0.55 - 0.65 pause: 0.01)										
	0.55	0.56	0.57	0.58	0.59	0.6	0.61	0.62	0.63	0.64	0.65
2008	0.62	0.62	0.61	0.6	0.6	0.59	0.58	0.58	0.57	0.56	0.55
2009	0.68	0.68	0.67	0.67	0.65	0.64	0.64	0.63	0.62	0.62	0.62
2010	0.66	0.65	0.65	0.65	0.64	0.64	0.63	0.63	0.62	0.62	0.61
2011	0.69	0.68	0.68	0.68	0.67	0.67	0.66	0.66	0.65	0.65	0.64
2012	0.67	0.66	0.66	0.66	0.66	0.66	0.65	0.65	0.65	0.64	0.64
2013	0.62	0.62	0.62	0.61	0.61	0.61	0.6	0.6	0.6	0.59	0.59
2014	0.51	0.5	0.5	0.49	0.49	0.48	0.48	0.47	0.47	0.46	0.46
2015	0.58	0.58	0.57	0.57	0.56	0.56	0.55	0.55	0.54	0.53	0.53
2016	0.66	0.67	0.67	0.66	0.66	0.65	0.65	0.64	0.64	0.63	0.62
2017	0.68	0.67	0.67	0.67	0.66	0.66	0.65	0.66	0.66	0.65	0.65
Mean	0.637	0.633	0.630	0.626	0.620	0.616	0.609	0.607	0.602	0.595	0.591

From Table 3, the DCC results for the *k* conditions from 0.55 to 0.65 were found to be similar. Because the aim was to gain as a high a value as possible, a DCC above 0.6 was considered too small. When k = 0.6, there was a high DCC, which was able to secure a large proportion of the Chinese regional data in equation (11). Based on the principles proposed above, the final equation for C-CDDs was determined:

$$C-CDDs = 0.6CDDs_{regional} + 0.4CDDs_{exsited} \tag{15}$$

4. 2 Test on American cities

To assure the feasibility of the proposed C-CDDs, we test the new weather indices proposed on some cities that have similar weather conditions with Shanghai, assuming these cities do not trade the weather derivatives contracts. Atlanta, which has similar weather conditions and high correlation coefficients of 0.9004 with Shanghai, was chosen as the center city to conduct the same analysis using the proposed equation (15). Little Rock and Raleigh were chosen as the matching cities, and Columbus and Mascon were chosen as the regional cities near to Atlanta that had similar weather conditions according to the monthly average temperatures over 25 years. The equation (15) was used to calculate the simulated daily C-CDDs in Atlanta and were compared with the real daily CDDs in Atlanta over ten years, the simulation results show they have similar fluctuation trends.

According to the RMSE data, the error in 2011 was the largest at 0.96, with the mean value of the RMSE over ten years being approximately 0.793. The RMSE in each year were all below 1, indicating that the simulation results were reasonable; therefore, it was believed that the same C-CDDs were feasible in the Shanghai market. The CDDs are cumulative cooling degree day indices, and the prior price settlement refers to the previous monthly cumulative CDDs. Therefore, it is also important to compare the cumulative CDDs in each month. The cumulative CDDs for each month over ten years were calculated and analyzed using equation (10) with the pause between T_1 and T_2 being one month. The mean values for each month were calculated and compared with the mean value of the cumulative CDDs in Atlanta. Then, absolute percentage error (APE) δ was utilized to determine the simulated and real value errors, the calculation for which was as follows:

$$\delta = \frac{|y - y*|}{y*} \tag{16}$$

where y represented the simulated cumulative CDDs and y^* represented the mean real value for the cumulative CDDs in Atlanta from 2008 to 2017 (ten years). The results are shown in Table 4.

Table 4. Mean monthly simulated CDDs and true value in Atlanta over ten years

Month	Monthly weather indices		
	Simulated values	True values	δ
Apr.	42.85	42.47	0.009
May.	124.7	124.46	0.002
Jun.	242.4	236.51	0.025
Jul.	280.25	266.13	0.053
Aug.	258.03	252	0.024
Sep.	164.72	165.86	0.007
Oct.	43.32	44.75	0.032

Table 5. Mean monthly simulated CDDs and true value in Las Vegas over ten years

Month	Monthly weather indices		
	Simulated values	True values	δ
Apr.	90.80	92.01	0.013
May.	212.04	222.96	0.049
Jun.	398.39	424.85	0.062
Jul.	461.36	512.57	0.100
Aug.	434.97	471.96	0.078
Sep.	312.64	337.14	0.073
Oct.	129.45	129.53	0.001

Table 6. Mean monthly simulated CDDs and true value in Little Rock over ten years

Month	Monthly weather indices		
	Simulated values	True values	δ
Apr.	36.31	36.04	0.007
May.	111.12	111.71	0.005
Jun.	240.19	251.76	0.046
Jul.	274.63	282.405	0.028
Aug.	254.70	264.89	0.038
Sep.	150.89	151.33	0.003
Oct.	37.23	36.1	0.031

From Table 4, it can be seen that in April, May and September, there were smaller errors than in other months and in July, the error was the largest at 5.3%. Besides testing Atlanta city, we also choose Las Vegas and Little Rock, which have similar weather conditions, to make sure the viability of proposed weather indices. We do the same experiments as we test on Atlanta and the results are shown in Table 5 and 6. It can be seen that, for

Las Vegas, in April and September, there were smaller errors than in other months and in July, the error was the largest at 10%. As for Little Rock, the error is much smaller in April, May and September and the largest is 4.6% in June. As the result of RMSE, the Las Vegas over ten years is approximately 1.505 and Little Rock is 0.90.

These results indicated that the simulated C-CDDs performed well and proved that it was feasible for regions in China such as Shanghai and its surrounding cities to introduce C-CDDs to hedge enterprise risk.

5. SIMULATION AND PROVE

To further analyze the C-CDDs and CDDs correlations in Las Vegas (CDDs-LV), the DCC-GARCH (*1*, *1*) model was used to simulate these two weather indices. The data range was set from 2008 to 2017 as a continuous sequence, with the data still being stationary 1st difference data. The two data sets had weak skewness, kurtosis, and normality and had a significant ARCH effect. Based on these characteristics, C-CDDs and CDDs-LV were simulated using the DCC (*1, 1*) and GARCH (*1*, *1*) models to determine the parameters for these two weather indices. For the C-CDDs the parameter α = 0.103, β = 0.842 and for the CDDs-LV α = 0.286, and β = 0.413. The parameter for DCC a was 0.032, and for b was 0.820, which indicated that the results were reasonable as the weather indices had a tight correlation, were stable and had strong continuity; therefore the feasibility of proposed C-CDDs was demonstrated.

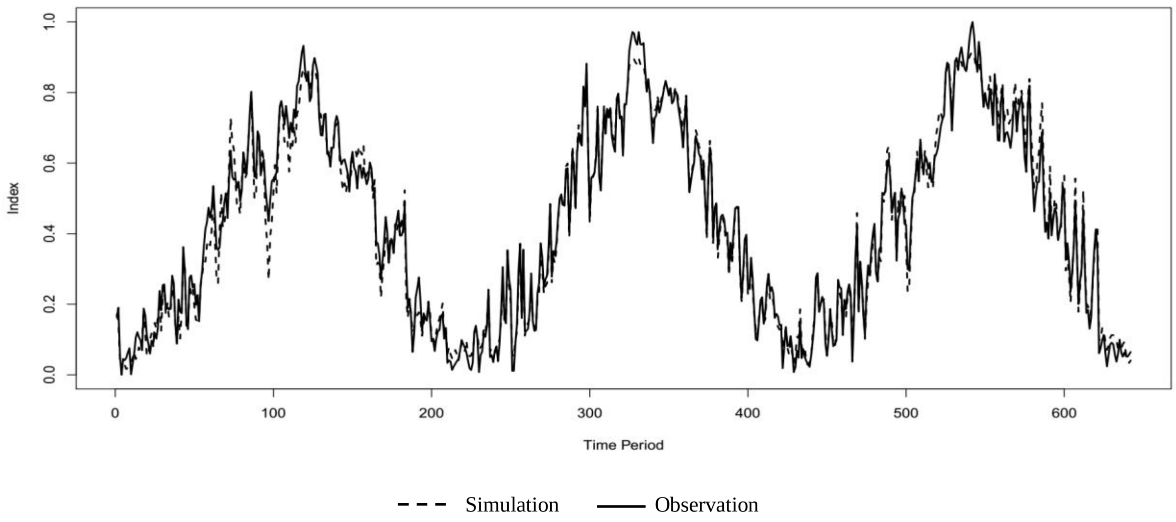

Figure 2: The simulation results of C-CDDs using ANNs

The ANNs was employed to simulate the C-CDDs in Shanghai, the temperatures in Hangzhou, Nanjing and Shanghai and the CDDs in Las Vegas and Little Rock as inputs, with the C-CDDs calculated using equation (15) being the outputs. The previous seven years data was used as the training sets, and the other data was the test set. The simulation for the test set is shown in Figure 2. The RMSE for the simulation was 0.025, and the R-square was 0.978. The simulation results were almost perfect, with a reasonable simulation degree. Only the temperatures in Hangzhou, Nanjing and Shanghai were then used as the inputs for the simulation, with the influence of the US weather indices excluded, as shown in Figure 3; the RMSE and R-square were 0.132 and 0.770. Compared with the previous simulation which included Hangzhou, Nanjing and Shanghai and the CDDs from Las Vegas and Little Rock as the inputs, the simulation degree was found to be worse and the RMSE was much higher.

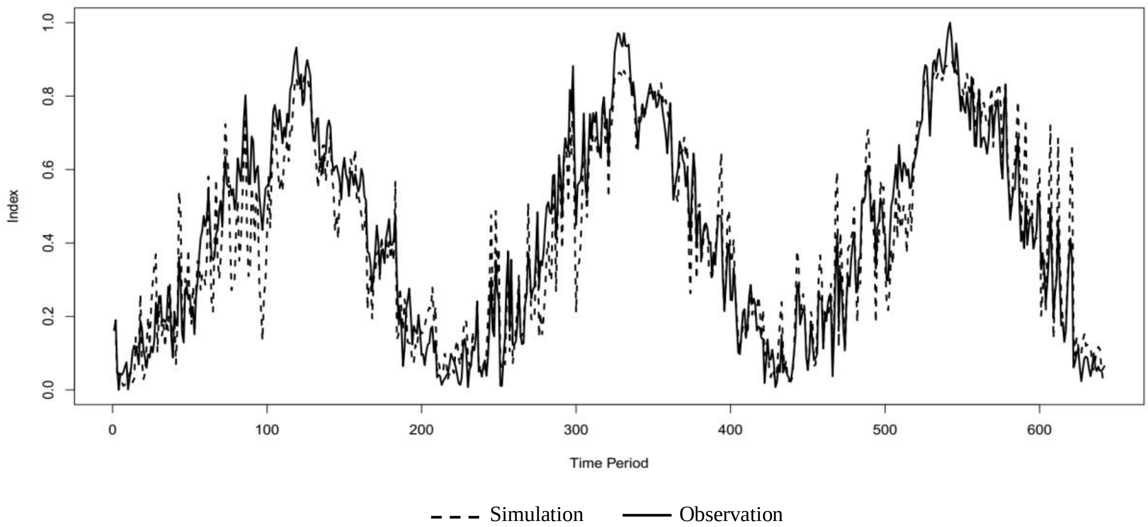

Figure 3: C-CDDs Simulation results using ANNs without US components

As the new weather indices were not predictable and lacked a unified market logic, the poor ANNs simulation results indicated there were design inefficiencies. The 100% fitness also indicated an over fitting as there was no natural variability or volatility. However, in general, the simulation showed that the proposed weather indices had the ability to express the market logic, and were accepted by the machine learning. The exclusion of the US weather indices illuminated some characteristics of the new weather indices. The influence of the US weather indices improved the simulation accuracy of the new weather indices by 21% with the other 77% being influenced by the regional weather in China.

The results of the deep machine learning showed that it was able to part predict the new weather indices and because the ANN performed well when learning the new weather indices, the new weather indices were considered stable and feasible. Therefore, the C-CDDs could be used to determine the prior prices for the weather derivative contracts.

6. CONCLUSION AND FUTURE WORKS

In this paper, a new weather index was proposed that combined Chinese regional weather conditions with US cities that already employed weather derivatives. Two principles were followed when creating the new weather indices and the influence of existing weather indices was added to improve feasibility. From the experiments, it was shown that the proposed weather indices were reasonable and feasible. The Atlanta, Las Vegas and Little Rock weather indices were included in a further assessment to test the suitability of the proposed weather indices for the Chinese derivatives markets, and the DCC-GARCH and ANN models were employed to demonstrate the feasibility, for which the error in the simulated results was found to be acceptable.

China's position as the core global supply chain country significantly influences international trade. Because of China's large land mass, there are varying weather conditions across the country, which can affect production; therefore, it would be sensible for enterprises dealing with China to hedge their risk by trading on the Chinese financial markets. While weather derivatives are being used in Japan, as there are only a few types, they do not cover all situations; therefore, it would be more convenient for surrounding countries to trade weather derivatives on the Chinese financial markets based on the variability in Chinese weather conditions. In future work, we plan to further develop the Chinese weather derivative markets to assist enterprises and especially energy firms efficiently hedge risk to avoid losses. The creation of the new weather indices may provide a well reference for Chinese financial markets to develop the Chinese weather derivative market, which can help managers well to hedge the risk brought by terrible weather. The policy maker could set the prior prices for the weather derivatives contracts, according to the weather indices we proposed, to help start trading weather derivatives in Chinese financial markets. The development of regional temperature indices could also provide inspiration to other large cities that do not have weather derivatives.

The proposed Chinese weather derivative indices were connected with the US market; however, European indices were not considered in this paper. However, with the expansion of "The Belt and Road" initiative, it is necessary to deepen cooperation with European countries, improve the development of the international financial markets, and ensure communication between the two regions.

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REFERENCES

[1] Gersema, G., Wozabal, D. (2017). An equilibrium pricing model for wind power futures. Social Science Electronic Publishing.

[2] Challis, Bright forecast for profits, reactions.

[3] H. M, Hedging the force of nature.

[4] A. Zapranis, A. Alexandridis (2010). Modeling and forecasting cumulative average temperature and heating degree day indices for weather derivative pricing. Neural Computing & Applications, 20(6): 787–801.

[5] Cramer, S., Kampouridis, M., Freitas, A. A., & Alexandridis, A. K. (2017). An extensive evaluation of seven machine learning methods for rainfall prediction in weather derivatives. Expert Systems with Applications, 85: 169-181.

[6] S. Liu, L. Wang, W. Huang (2017). Effects of process and outcome controls on business process outsourcing performance: Moderating roles of vendor and client capability risks. European Journal of Operational Research, 260(3): 1115–1128.

[7] Su, L. (2011). A Rule Extraction Based Approach in Predicting Derivative Use for Financial Risk Hedging in Construction Companies. International Conference on Information Management, Innovation Management and Industrial Engineering IEEE, 6510-6514.

[8] Buchholz, M., & Musshoff, O. (2014). The role of weather derivatives and portfolio effects in agricultural water management. Agricultural Water Management, 146(146): 34-44.

[9] Hong, S. J., & Sohn, S. Y. (2013). Peer group analysis for introducing weather derivatives for a city. Expert Systems with Applications, 40(14): 5680-5687.

[10] Benth, J. Å., Benth, F. E., & Jalinskas, P. (2007). A spatial-temporal model for temperature with seasonal variance. Journal of Applied Statistics, 34(7): 823-841.

[11] Turvey, C. G., & Kong, R. (2010). Weather risk and the viability of weather insurance in china's gansu, shaanxi, and henan provinces. China Agricultural Economic Review, 2(1): 5-24.

[12] Zong, L., Ender, M. (2016). Spatially-aggregated temperature derivatives: agricultural risk management in China. International Journal of Financial Studies, 4(3).

[13] Tim Bollerslev. (1986). Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics, 31(3):

307-327.

[14] Robert F. Engle. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of united kingdom inflation. Econometrica, 50(4): 987-1007.

[15] Hou, Y., Li, S. (2016). Information transmission between u.s. and china index futures markets: an asymmetric dcc garch approach . Economic Modelling, 52: 884-897.

[16] R. F. Engle. (2002). Dynamic conditional correlation: A simple class of multivariate garch models. Business and Economic Statistics, 20 (3): 339350.

[17] Y. Tsukuda, J. Shimada, T. Miyakoshi. (2017). Bond market integration in east asia: Multivariate garch with dynamic conditional correlations approach. International Review of Economics & Finance 51: 193–213.

[18] X. Zhong, D. Enke. (2017). A comprehensive cluster and classification mining procedure for daily stock market return forecasting. Neurocomputing.

[19] A. Zapranis, A. Alexandridis. (2009). Weather derivatives pricing: Modeling the seasonal residual variance of an ornsteinuhlenbeck temperature process with neural networks. Neurocomputing, 73(13): 37–48.

[20] A. K. Alexandridis, M. Kampouridis, S. Cramer. (2017). A comparison of wavelet networks and genetic programming in the context of temperature derivatives, International Journal of Forecasting, 33(1): 21–47.