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An Approach to Quantify the Heat Wave Strength and Price a Heat Derivative for Risk Hedging

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ABSTRACT

Mitigating the heat stress via a derivative policy is a vital financial option for agricultural producers and other business sectors to strategically adapt to the climate change scenario. This study has provided an approach to identifying heat stress events and pricing the heat stress weather derivative due to persistent days of high surface air temperature (SAT). Cooling degree days (CDD) are used as the weather index for trade. In this study, a call-option model was used as an example for calculating the price of the index. Two heat stress indices were developed to describe the severity and physical impact of heat waves. The daily Global Historical Climatology Network (GHCN-D) SAT data from 1901 to 2007 from the southern California, USA, were used. A major California heat wave that occurred 20–25 October 1965 was studied. The derivative price was calculated based on the call-option model for both long-term station data and the interpolated grid point data at a regular $0.1^\circ \times 0.1^\circ$ latitude–longitude grid. The resulting comparison indicates that (a) the interpolated data can be used as reliable proxy to price the CDD and (b) a normal distribution model cannot always be used to reliably calculate the CDD price. In conclusion, the data, models, and procedures described in this study have potential application in hedging agricultural and other risks.

Key words: heat derivative price, heat wave risk, cooling degree day, call option, payoff, southern California

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1. Introduction

Heat stress is an important factor of agricultural and economic loss. Under the scenario of global climate change and water shortage, the drought and heat stress impact to the economic loss is likely to increase in the future. The impact of climate on rural income in developing countries has been quantified using satellite remote-sensing data (Mendelsohn et al., 2007). Mitigating the heat stress by adopting appropriate insurance or derivative policies is a vital financial option for various sectors (Jewson and Brix, 2005; Dorfleitner and Wimmer, 2010). The purpose of this study was to develop an approach to assessing the strength of a heat wave and to pricing the heat stress derivative based on degree days. This approach can be applied to agriculture, energy, health, and other business sectors.

The impact of heat stress is inhomogeneous around the world. Population increase and agricultural expansion are two major anthropogenic factors. The population increase in southern California, USA, has been rapid. The population increased from 14.6 million in 1990 to 16.5 million in 2000, representing 13% growth in the 1990s in addition to 26% growth in the 1980s. This population growth has created unprecedented challenges and opportunities to California's society and economy (SCAG, 2008). Innovative methods of coping with the impact of heat stress on agriculture, economic development, water supply, and human life need to be developed. These methods need to consider optimal electrical power supplies, water sources, and other heat mitigation aspects. Sustainable business plans call for risk hedging and assessments based on historic weather data (Kramps, 2008) and climatic projections (Miller et al., 2008).

Until recently, insurance was the main tool providing economic protection against extreme weather conditions. However, insurance is a direct damage re-

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covery tool, and the corresponding risk management is based on the damage assessment. Thus, insurance typically covers only high-risk events that occur with relatively low probabilities, such as extreme drought, flooding, and tornados. It does not provide protection against decreasing business demands due to unfavorable weather conditions. These low-risk and relatively high-probability events can cause significant and unfavorable revenue fluctuations for many businesses and industries, as well as agriculture producers. Weather derivatives can be used as a tool to reduce the volatility of business revenue. A weather derivative product is based on a meteorological index, such as extreme temperature, extreme precipitation, extreme wind gust, and cooling degree day (CDD). The index can be used in the market in a way similar to stocks or other commodity indices. The traded product is the weather derivative, which is used to hedge weather risks.

This study focused on risk hedging of heat waves in the state of California, USA. Heat stress index (HSI) and modified heat stress index (mHSI) were used as the severity indicators of a heat wave. The heat indices used on the current weather derivative market are CDD and HDD (heating degree day). The heat stress indices, including HSI and mHSI, have not been used in the market yet, although they are sensitive heat stress indicators and have market potential. Therefore, in this study we used CDD as the hedging index, and it was priced. The CDD is the positive difference between a hot day's mean temperature and a baseline temperature, usually set at 18°C. The CDD is a clear measure of the warmness of a day with respect to a baseline temperature. Therefore, CDD is a commonly used commercial trade index that reflects the agricultural water usage in semiarid areas like California or that reflects the energy demand for air conditioning. We used long-term airport weather station observations as benchmark data; they are more reliable and of higher quality relative to other short-term station measurements. We identified the heat waves observed at the international airports of Los Angeles, San Diego, and San Francisco since 1939, and we investigated the impact of the heat in each area. We determined a method for calculating the premiums of the weather derivative pricing based on the historical weather data and based on a theoretical model. In addition, for applicability of our weather derivative pricing, we also interpolated the observation data to a $0.1° \times 0.1°$ latitude–longitude grid across California, which helped us to identify the spatial impact of the heat waves. Our study was based on the daily observation data of maximum and minimum temperatures acquired from the Global Historical Climatology Network-Daily (GHCN-D) (Durre et al., 2008) for the period of 1 January 1901 to 31 December 2007.

The rest of the paper is arranged as follows. Section 2 describes data and California heat waves; section 3 describes the calculation method for weather derivative premiums and its results; and section 4 presents discussion and conclusions.

2. Data

The GHCN-D data were used in this study (Peterson and Vose, 1997; Durre et al., 2008). This dataset, compiled by the US National Climatic Data Center, is the most comprehensive global daily station data of daily maximum temperature, minimum temperature, precipitation, snowfall, and snow depth. It includes observation reports from more than 40 000 stations around the world. The history of the number of the GHCN-D stations in California is shown in Fig. 1. The GHCN-D record for California started in 1877. The station is located in Sacramento (38.58°N, 121.15 °W) and is still operating. The number of operating observation stations in California reached its maximum between 1960 and 1970, with 422 temperature stations in 1970 and 674 precipitation stations in 1960. The number of stations has since declined to the current level of ∼300 for temperature and ∼400 for precipitation. For our weather-derivative pricing, we used the observation data from in the interval 1 January 1901 to 31 December 2007.

In Fig. 2, the spatial distribution of the stations reporting temperature is shown for 4 different years

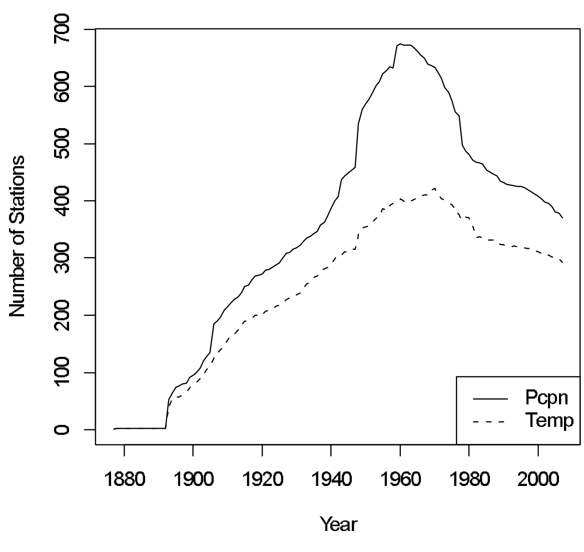

Fig. 1. History of the total number of temperature and precipitation stations in California from the GHCN-D dataset between 1877 and 2007. The dashed line indicates the number of surface air temperature stations and the solid line is for the number of precipitation stations.

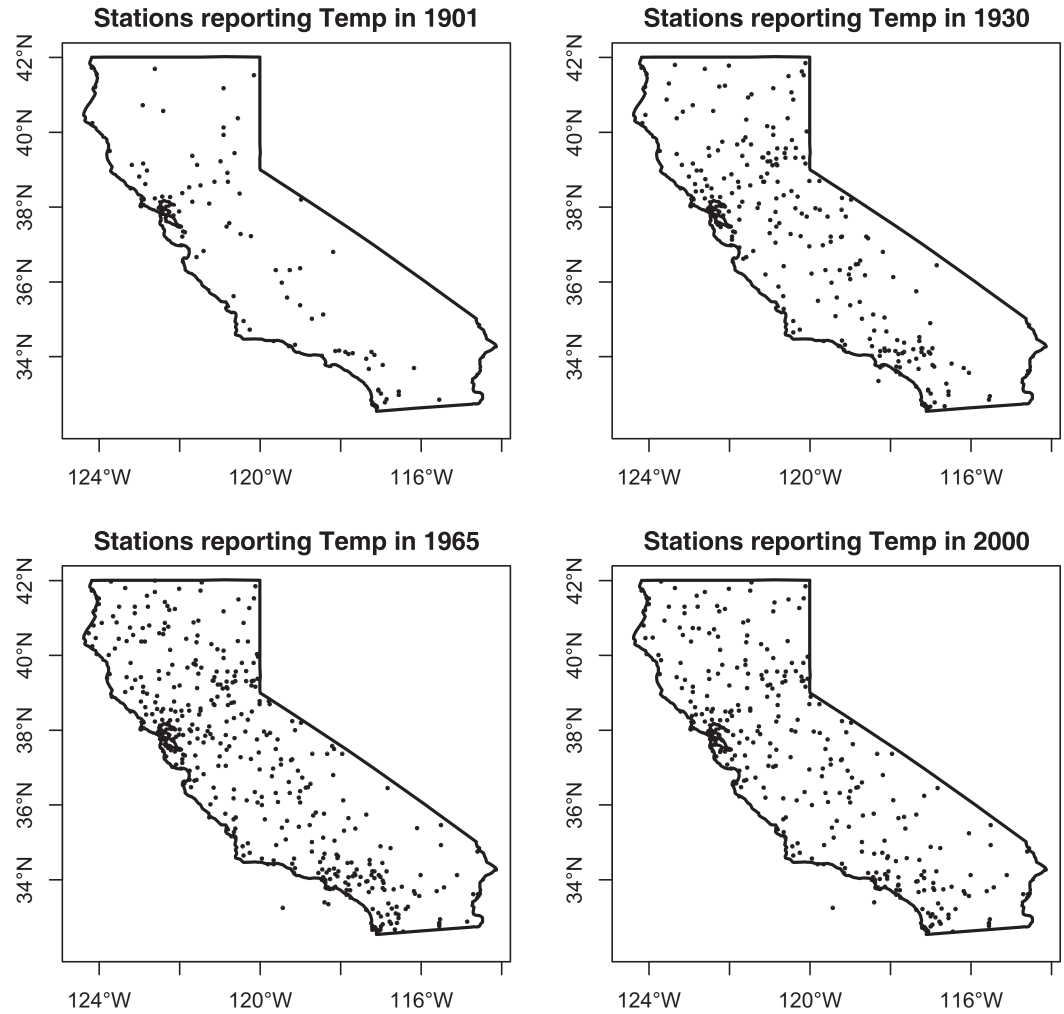

Fig. 2. The spatial distribution of the GHCN-D temperature weather stations in California in different years.

(i.e., 1901, 1930, 1965, and 2000), varying from the time of sparse coverage to the time of dense coverage. Each the station marked in the figure reported temperature data at least once in the given year. The San Francisco area has been well covered since 1901. The southeastern desert areas were not covered in the earlier years of this period. Although the year 2000 had $\sim$100 fewer stations than 1965, the spatial coverage of these 2 years was about the same. Some observations at redundant stations in the San Francisco and Los Angeles areas were discontinued.

The heat effect on people and crops during a heat wave is often a composite factor of surface air temperature (SAT) and relative humidity (RH) that can be measured by a heat index (HI), a nonlinear regression of these two basic factors (Steadman, 1979). For California, humidity is usually not a large factor during a summer heat wave because the California summer is very dry and has little precipitation. In Southern California, total precipitation during the 6 months of the dry season (May–October) is characteristically $<15\%$ of the annual total. In particular, humidity is low in the inland areas; it can be $<15\%$ during the hottest hours of a day in the summer in many inland areas, and it is generally $<40\%$ in almost all the inland areas (Gaffen and Ross, 1999). Although the humidity can be high in the afternoon in the coastal areas, the temperature is also lower in these areas. Thus, humidity does not play a major role in California heat-wave impact, and we used only temperature data to identify the heat waves from 1901 to 2007.

The World Meteorology Organization (WMO) defines a heat wave as a period of >5 consecutive days where the daily maximum temperature $T_{\max}$ exceeds its climatology $T_{\max,\mathrm{clim}}$ by 5°C (Frich et al., 2002). The daily climatology was calculated as the 30-year mean daily maximum temperature $T_{\max}$ during 1961–1990. This definition is different than that used by the US National Weather Service, which defines a heat wave as an event of maximum temperature >40.6°C (or 105°F) and minimum temperature > 26.7°C (or 80°F) for 2 consecutive days. The problem with fixed thresholds like these is that some parts of the United States frequently exceed the thresholds, but damage does not occur because both human and agriculture have already adapted to the local climate. Hence the severity and impact of a heat wave can be measured by a heat stress index (HSI)

$$\mathrm{HSI} = \sum_{k=1}^{K} [T_{\max}(k) - T_{\max,\mathrm{clim}(k)]} \ ,(1)$$

where each term in the sum is the daily maximum temperature anomaly and is hence $\geqslant 5$, K is the total number of days of a heat wave and $\geqslant 5$, and k is the count for the kth day into a heat wave. The heat waves detected at Los Angeles International Airport (LAX) and San Diego Lindbergh Field International Airport (SAN) are listed in Table 1. Although the distance between LAX and SAN is only 200 km, LAX experienced eight heat waves, while San Diego experienced only five in the same period, 1965–2007. This may be due to the fact that SAN is very close to ocean, only a few hundred meters from the San Diego Bay. The maximum HSI was 98.5°C for the LAX's 19 September 1978 (19.09.1978) heat wave, and was 88.5°C for SAN's 20 October 1965 (20.10.1965) heat wave. The more recent heat waves in northern California reported at the San Francisco International Airport (SFO) (e.g., 1997, 2004, and 2006) were not recorded at LAX and SAN. However, due to the low temperature of the SFO climatology in the summer, the impact was weak.

The analysis given by Steadman (1979) showed that heat impact can be a nonlinear function. Here we introduce a modified heat stress index (mHSI) defined by the following formula:

$$\mathrm{mHSI} = \sum_{k=1}^{K} T_{\max}(k)[T_{\max}(k) - T_{\max,\mathrm{clim}(k)]} \ .(2)$$

This index reflects the nonlinearity of the impact of a heat wave to society, agriculture, business, and industry. The values of both HSI and mHSI for the LAX and SAN heat waves are shown in Table 1. The spatially impacted area of the large-scale 20–25 October 1965 heat wave is shown in Fig. 3. This was among the strongest heat waves in California since 1901 (Gershunov et al., 2009), impacting nearly 0.3 million km^2, ~70% of the entire state of California. The HSI, mHSI, and the heat wave coverage data were helpful in determining the severity of the historic heat waves and the need for heat-stress risk management policies. During this 1965 heat wave, San Diego had an extremely high mHSI value of 2608.9. On 15 September 1939 (15.09.1939), and another heat wave was even stronger, with mHSI = 2278. This was caused by both high SAT and high SAT anomalies, because September is usually the hottest monthly in San Diego.

3. Method for pricing the CDD call option

HSI and mHSI can be used to measure the severity of heat waves, and they may provide information on the impact of the heat waves to agriculture and industry. However, these two indices have not been used in the market yet. A hedging market can only be explored for an index that is currently traded, which is CDD in our case.

Table 1. Heat waves at LAX and SAN airports.

Start Date (dd.mm.yyyy)		Duration (units：d)	HSI value (units: °C d^{-1})	mHSI value (units：°C °C d)
Los Angeles	20.10.1965	7	78.3	1829.8
	25.09.1970	6	52.0	1280.5
	23.06.1976	6	52.2	1213.5
	19.09.1978	10	98.5	2465.1
	13.09.1979	7	65.3	1576.3
	13.06.1981	6	74.3	16412.0
	04.09.1984	6	53.4	1328.1
	12.08.1994	6	47.7	1166.5
San Diego	15.09.1939	9	92.1	2278.0
	10.10.1939	6	49.1	1164.0
	20.10.1965	10	88.5	2068.9
	01.11.1976	8	70.0	1556.5
	17.06.1978	8	52.2	1170.8
	20.09.1978	7	60.1	1378.9
	14.09.1979	6	54.8	1347.3

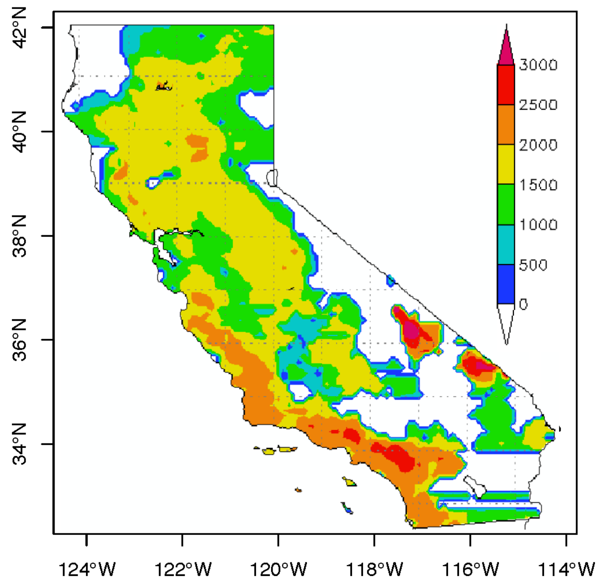

Fig. 3. Impacted area of the heat wave during 20–25 October 1965. The color legend indicates the mHSI values of the heat wave. The map is generated from the mHSI values calculated at every grid point.

The mathematical formula for calculating CDD for a day i at a specific location is

$$\mathrm{CDD}_i = \begin{cases} T_i - 18 & \text{if} \quad T_i > 18 \\ 0 & \text{else} \quad 0 \end{cases}, \tag{3}$$

where

$$T_i = \frac{T_{i,\max} + T_{i,\min}}{2} \tag{4}$$

is defined as the daily mean temperature, and $T_{i,\max}$ and $T_{i,\min}$ are this location's daily maximum and minimum near surface air temperature measured in degrees Celsius.

The index values are defined as the CDD sum of all degree days over a period of N days. The existing CDD contracts traded on market are usually for the summer season from May to September. The seasonal CDD index is the sum of the monthly CDD values [see Eqs. (6.5) and (6.6) in Kramps (2008)].

An option is a financial instrument that gives the right, but not the obligation, to engage in a future transaction on some underlying security. The purchaser of an option pays an up-front cash premium to the seller for price protection. For the weather derivative considered here, at the end date of the contract, the purchaser receives a certain amount of money, called payoff, if the weather index exceed the strike value in the contract period. Two options are considered here: call option and put option. The call option allows the buyer the right to buy a commodity, and the put option allows the buyer the right to sell a commodity.

We use x to denote the CDD. A call-option model for the payoff $p(x)$ may be written as follows:

$$p(x) = \begin{cases} 0 & \text{if} \quad x < K \\ D(x-K) & \text{if} \quad K \leqslant x \leqslant L \\ L_\$ & \text{if} \quad x > L \end{cases}, \tag{5}$$

where x is the seasonal CDD value, K is the strike at which the payoff starts from the option seller, D is the tick that gives the proportion of the payoff increase as the unfavorable weather condition, measured by x, gets worse, and the payoff is capped by $L_\$$ when the bad weather condition exceeds a threshold: $x > L_\$$. This model is shown in Fig. 4. The buyer pays a premium to the seller at the beginning of a contract. At the end of the contract period, the buyer receives zero payoff for favorable weather or maximum payoff $L_\$$ for a disastrous weather condition exceeding a certain level. Thus, the call option provides a mechanism of revenue protection to the buyer against unfavorable or even a disastrous weather. The CDD call option may be used by crop producers to protect their income against loss of crops due to excessive heat or by utility companies to protect their power transmission facility from damage costs caused by extremely high and suddenly imposed load for additional cooling. The buyer may receive some revenue from a significant loss due to bad weather. The seller may profit from the premium minus the minor payoff when the weather is good or insignificantly bad. Thus, the weather risk is hedged.

To provide a hypothetical illustration, we have chosen the example of a revenue protection policy purchased by an organic vegetable producer against loss due to excessive heat. The essentials of a sample CDD call option contract are given in Table 2. The crops in our illustration were hypothetically grown across the eastern area of Los Angeles, and the LAX airport temperature was used as a good proxy of surface air

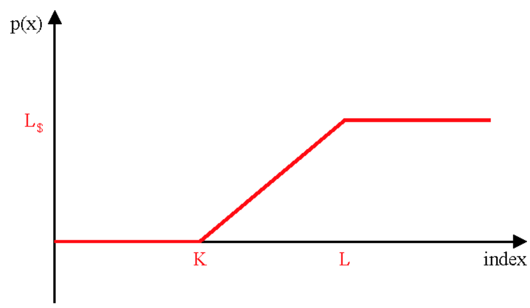

Fig. 4. A call option model. Here, K is the strike, and $L_\$$ is the maximum payoff.

Table 2. Format of a CDD call option contract.

CDD Call Option	
Current Time	28 February 2008
Location	Los Angeles LAX Airport
WMO Station ID	42500045114
Long Position	Organic Veggie Inc.
Short Position	ABC Bank
Accumulation Period	1 May 2008 to 30 September 2008
Underlying	Seasonal CDD
Variable	Daily surface air mean temperature measured in tenth of degree Celsius
Tick Size	US$100.00
Strike Level	332°C
Actual Level	359°C

temperature. The LAX historical data from 1945 to 2007 were applied. For the LAX data from May to September, the mean and standard deviation of CDD calculated for 63 years of data were 305°C and 107°C, respectively (Kramps, 2008). The agreement was set at 25% above the mean, of 332°C. The 2008 summer was hotter than normal, and the actual 2008 May–September CDD was 359°C. Thus, the Organic Veggie Company received a payoff of $2700, which is $ (359–332) × 100 at the end of the contract.

The parameters of the above call-option model should be optimized according to the historic data of both weather and economic loss in order for the market to be sustainable. However, with reasonably assumed parameters from experience, the fair price can be derived depending on the model parameters. Thus, the call options traded at different markets may use different parameters, depending on the needs of the dealer and the buyer. The call-option model with specific parameters can become proprietary to its developer or its dealer.

But how much should the Organic Veggie Company pay for the premium at the time of signing of the contract? To price the call option, the premium is determined according to the historic data using the following procedures. The fair premium is the expected payoff according to the historic data. The seller may add a profit margin and an overhead expense on the fair premium. We chose the LAX station as our example. The station is located at 33.93°N, 118.4°W, and its WMO ID is 42500045114. The seasonal CDD was calculated from 1945 to 2007 for the period of 1 May to 30 September. The top two panels of Fig. 5 show the historic values of CDD, the strike level, and the payoff amount. For a given year, when CDD value is above the strike level, a payoff will occur. Thus, every black dot above the blue line corresponds to the red line. The height of the red line reflects the payoff amount. The mean of the payoffs was US$32.29 according to this dataset, and this is the fair premium. The actual premium was 20% of the payoff standard deviation above this value or at another percentage higher than this value because of seller's profit and overhead expenses. The payoff standard deviation from this dataset was US$59.28. If the overhead is 20% of standard deviation, then the actual premium would be US$44.15 (=US$32.29+US$59.28×20%).

The bottom panels of Fig. 5 show the histograms of the payoff. Using this histogram we also calculated the expected value, which was approximately equal to the mean payoff described previously:

$$P = \sum_{m=1}^{M} q(m) f(m) \,. \tag{6}$$

Here, m is the index number of the bin on the horizontal axis of the lower panels in Fig. 5, $q(m)$ is the payoff for the bin m, $f(m)$ is the percentage frequency of the bin m, and M is the total number of bins (i.e., 10) in Fig. 5.

The standard deviation can also be calculated using this moment method. This calculation approach provides a way to calculate the premium from an assumed probability distribution model when the historic data are not available (see, e.g., Fig. 6).

It is desirable for both seller and buyer to have a long, complete data stream and spatially well-covered data to have a reliable assessment of the risk and accurate estimate of the premium. However, neither every location was covered by a station, nor did every station provide complete data from its beginning to its end. Thus, it was very important to interpolate the data onto a dense grid with reasonable accuracy (Shen et al., 2001). The California station data were interpolated onto a 0.1°×0.1° latitude–longitude grid using the inverse distance weighting method with a length scale (Shen et al., 2001; Kramps, 2008). Thus, interpolated data were used for the fair premium calculation. We interpolated data for the period 1 January 1901 to 31 December 2007. The CDD and payoffs calculated

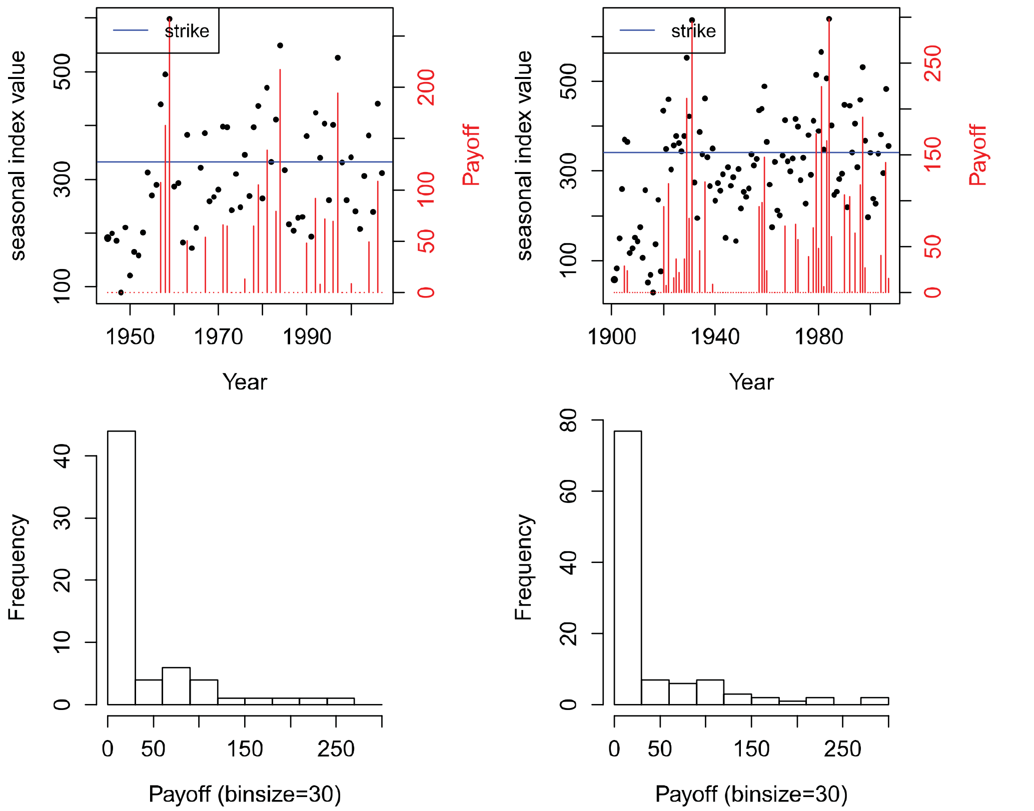

Fig. 5. Top-left panel: LAX CDD and payoff from station data. The black dots are the seasonal CDDs of the LAX station from 1945 to 2007. The horizontal blue line is the strike level. The dots are the historical CDD values whose ticks on the left hand side. The vertical red lines are the payoff values whose ticks are on the right hand side. Top-right panel: LAX CDD and payoff from the gridded data. Bottom-left panel: Histogram of payoffs calculated from the LAX station data. Bottom-right panel: Histogram of payoffs calculated from the LAX grid data.

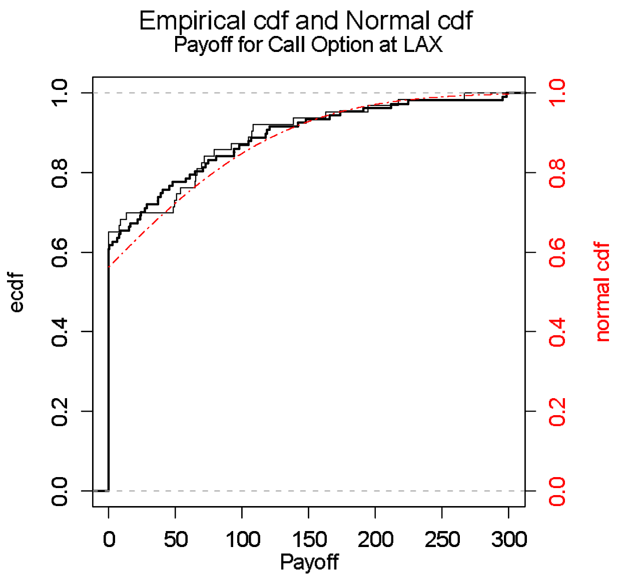

Fig. 6. Comparison of the payment CDF based on a CDD normal distribution models (thin dot-broken line), and the payment CDFs calculated from LAX station data (thick solid line) and gridded data (thin solid line).

based on the interpolated LAX data are shown in the top-right panel of Fig. 5. Based on the gridded data, the mean and standard deviation of the CDD were 310°Cand 124°C, respectively. The mean and standard deviations of the payoffs became US$33.79 and US$63.32, respectively. The actual premium was then US$46.45. This was slightly higher than the station data result of US$44.15.

The two premiums above appear low, considering the payoff in Fig. 5, because of the climate change to a warmer phase (Shen et al., 2005; Jewson and Penzer, 2006). The fair premium was computed when considering climate conditions in the cold phases in the 1910s and/or 1960s. Thus, the actual premium should have been much higher than the two calculated previously. The higher probability of summer hot days in the future years should have been taken into account. There are many ways to incorporate this information. In this study we developed a way that uses a climate distribution model and considers a climate shift. If climate change into a warmer phase is considered, a regression according to time may be used to increase this premium as time progresses.

For this initial study, we assumed a normal distribution of the seasonal CDD, and we calculated the payoffs according to the normal distribution model. Then we compared the model results with the results from the station data and the grid data. The CDD normal distribution is given by $N_{\mu,\sigma}(x)$, where x stands for CDD values with the mean μ and the standard deviation σ is being estimated from the station data. The cumulative distribution function (CDF) of the payoff is

$$F(p) = \begin{cases} 0 & \text{if} \quad p < 0 \\ C_{\mu,\sigma}(K + p/D) & \text{if} \quad 0 \leqslant p < L_{\$} \\ 1 & \text{if} \quad p \geqslant L_{\$} \end{cases} . \tag{7}$$

Here $C_{\mu,\sigma}(x)$ is the cumulative distribution function for the normal distribution. In this formula, all the parameters are computed from data and are the same as those used previously. When the historic data are unavailable, the values for these parameters can be assumed based on similar climate and crop conditions. Figure 6 shows a comparison of the CDF from the model and from the station and gridded data. The good fit of the three curves provides confidence in the model for the LAX station. The accumulated payoff probabilities have noticeable differences for smaller payoffs, where the normal model CDF is below the CDF based on the historic weather data. The difference becomes smaller when the payoff becomes larger.

Another measure of the difference can be made using PDF (probability density function) rather than CDF. That may better show the differences at the right tail. However, the financial market cares more about the CDF results, which motivates users to track the CDF differences.

The normal distribution model was a trial model for this initial study and may not work for every location. Our numerical tests show a good fit for San Diego (SAN) airport. However, the fit for San Francisco SFO airport was not as good. The lesser fit may be due to the lower temperature climatology at SFO (Kramps, 2008). Whether a nonparametric distribution model for pricing the CDD or even mHSI can be developed should be investigated in the future.

4. Conclusions and discussion

We used HSI and mHSI to quantify the severity of a heat wave and developed an approach to price the CDD weather derivative that hedges the risks due to heat stress during the period of persistent abnormally high surface air temperature. A call-option model was used as an example of calculating the index price. The daily Global Historical Climatology Network (GHCN-D) SAT data from 1901 to 2007 were used in the focused study region of California, the United States. A major California heat wave of 20–25 October 1965 was revealed and was used to demonstrate our theory. The derivative price was calculated based on the call option model for both long-term station data and the interpolated grid point data at a regular $0.1° \times 0.1°$ latitude–longitude grid. The resulting comparison indicates that (a) the interpolated data can be used as reliable proxy to price the CDD, and (b) a normal distribution model cannot always be used to reliably calculate the CDD price. In conclusion, the data, models, and procedures developed in this study have potential applications in hedging agricultural and other risks.

Seasonal CDD is a commonly used trade tool and is priced here for California, USA. However, a short time period CDD contract can be designed only for the heat-wave period and price the CDD derivative can be calculated accordingly.

The GHCN dataset is valuable in weather risk hedging due to many factors because it has a long history and global coverage. The GHCN data may be used to calculate weather derivatives over regions other than California or the United States, although the data coverage in other regions may not be as good. An analytic model with some station calibration and data interpolation may be beneficial.

The physiological mechanisms of the nonlinear index mHSI or even linear index HSI have not yet been investigated. A comprehensive study of plant physiological data, temperature data, and humidity data may be helpful to justify the applications of mHSI and to create a market for the mHSI trade, and hence to develop a price system for mHSI.

Many weather risks and option models can be developed from the station data, gridded data, and assumed models. Future studies may generate more examples over various regions around the world for practical applications. It may be worthwhile to develop a pilot market application for this type of weather derivative for the emerging integrated agricultural business for the northeastern China to safeguard the stability of the region's agricultural production (Dorfleitner and Wimmer, 2010).

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REFERENCES

Dorfleitner, G., and M. Wimmer, 2010: The pricing of temperature futures at the Chicago Mercantile Exchange. *Journal of Banking and Finance,* **34**, 1360–1370.

Durre, I., M. J. Menne, and R. S. Vose, 2008: Strategies for evaluating quality assurance procedures. *J. Climate Appl. Meteor.*, **47**, 1785–1791.

Frich, A., L. V. Alexander, P. Della-Marta, B. Gleason, M. Haylock, A. M. G. Klein Tank, and T. Peterson, 2002: Observed coherent changes in climatic extremes during the second half of the twentieth century. *Climate Research,* **19**, 193–212.

Gaffen, D. J., and R. J. Ross, 1999: Climatology and trends of U.S. surface humidity and temperature. *J. Climate,* **12**, 811–828.

Gershunov, A., D. R. Cayan, and S. F. Iacobellis, 2009: The great 2006 heat wave over California and Nevada: signal of an increasing trend. *J. Climate,* **22**, 6181–6203.

Jewson, S., and A. Brix, 2005: *Weather Derivative Valuation: The Meteorological, Statistical, Financial and Mathematical Foundations.* Cambridge University Press, 373pp.

Jewson, S., and J. Penzer, 2006: Estimating trends in weather series: Consequences for pricing derivatives. *Studies in Nonlinear Dynamics and Econometrics,* **10**(3), Article 9.

Kramps, B., 2008: *Daily California Temperature and Precipitation Data Gridding and Its Applications.* Master Thesis, San Diego State University, USA, 178pp.

Mendelsohn, R., A. Basist, P. Kurukulassuriya, and A. Dinar, 2007: Climate and rural income. *Climatic Change,* **81**, 101–118.

Miller, L.M., K. Hayhoe, J. Jin, and M. Auffhammer, 2008: Climate, extreme heat, and electricity demand in California. *J. Appl. Meteor.,* **47**, 1834–1844.

Peterson, T. C., and R. S. Vose, 1997: An overview of the Global Historical Climatology Network temperature data base. *Bull. Amer. Meteor. Soc.,* **78**, 2837–2849.

SCAG, 2008: Southern California Association of Governments, resolving regional challenges. [Availble online from http://www.scag.ca.gov/census/]

Shen, S. S. P., P. Dzikowski, G. Li, and D. Griffith, 2001: Interpolation of 1961–1997 daily climate data onto Alberta polygons of ecodistrict and soil landscape of Canada. *J. Appl. Meteor.* **40**, 2162–2177.

Shen, S. S. P., H. Yin, K. Cannon, A. Howard, S. Chetner, and T. R. Karl, 2005: Temporal and spatial changes of agroclimate in Alberta during 1901–2002. *J. Appl. Meteor.,* **44**, 1090–1105.

Steadman, R. G., 1979: The assessment of sultriness. Part I: A temperature-humidity index based on human physiology and clothing science. *J. Appl. Meteor.*, **18**, 861–873.