Systemic Weather Risk and Crop Insurance: The Case of China

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October 26, 2010

The supply of affordable crop insurance is hampered by the existence of systemic weather risk which results in large risk premiums. In this article, we assess the systemic nature of weather risk for 17 agricultural production regions in China and explore the possibility of spatial diversification of this risk. We simulate the buffer load of hypothetical temperature-based insurance and investigate the relation between the size of the buffer load and the size of the trading area of the insurance. The analysis makes use of a hierarchical Archimedean copula approach (HAC) which allows flexible modeling of the joint loss distribution and reveals the dependence structure of losses in different insured regions. Our results show a significant decrease of the required risk loading when the insured area expands. Nevertheless, a considerable part of undiversifiable risk remains with the insurer. We find that the spatial diversification effect depends on the type of the weather index and the strike level of the insurance. Our findings are relevant for insurers and insurance regulators as they shed light on the viability of private crop insurance in China.

Keywords: crop insurance, systemic weather risk, hierarchical Archimedean copulas
JEL Classification: C14, Q19

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1 Introduction

China is one of the world's largest agricultural producers. Its share in the world production of cereals, for example, amounted to about 20 % in 2004. At the same time agricultural producers in this country are exposed to pronounced yield risks, particularly weather risks (The World Bank, 2007; Turvey and Kong, 2010). Thus, agricultural insurance can play a vital role in stabilizing the agro-food economy, especially in stabilizing the income of farmers and stimulating investment in agriculture. Nevertheless, the agricultural sector in China currently appears to be under-insured: only 0.2 % of the agricultural GDP was covered by insurance in 2007 (Swiss Re, 2009). In 2005, the national agricultural insurance premium volume was $91 million, representing a mere 0.6 % of total Chinese non-life insurance premiums. The market for these products took off since the Chinese government began to subsidize insurance premiums. Nonetheless, the agricultural insurance market in China is still at an infant stage. Currently, several agricultural insurance concepts are piloted in China. The models range from specialized mutual insurance companies with local government subsidies to foreign commercial insurance companies without public subsidies. However, the World Bank (2007) asserts that the existing agricultural insurance schemes are still too expensive for Chinese agricultural producers. The observation that there is an obvious gap between the willingness to pay for agricultural crop insurance and the willingness to accept for such insurance is not specific for China. For many countries around the world, either low participation rates for unsubsidized (multi-peril) crop insurance or high premium subsidies can be found (Diaz-Caneja et al., 2009). There are two arguments in the insurance literature to explain this fact. The first argument refers to moral hazard behavior of farmers resulting in large transaction costs or deductibles (Goodwin, 2001); however, this problem could be mitigated by using index-based insurance such as area yield insurance or weather derivatives (Hellmuth et. al., 2009). The second obstacle for an implementation of crop insurance is the systemic risk inherent to crop failures. In this paper we explore this argument and check its validity for China.

The objective of this paper is to determine the spatial dependence of weather events in different regions in China and the associated joint losses of a hypothetical crop insurance written on these weather events. In particular, we investigate how effective risk pooling is when the trading area of the insurance increases. For this purpose we estimate the joint occurrence of unfavorable weather conditions at different regional levels. We are particularly interested in the tail behavior of the joint loss distribution because the probability of large losses is crucial for the required buffer fund of the insurer and thus for premium loading. These parameters, in turn,

affect the viability of index-based crop insurance. Analyzing weather variables instead of agricultural yields is advantageous from a statistical viewpoint since daily data can be used instead of annual data, resulting in a much longer time series. Moreover, this approximation is reasonable because the stochasticity of crop yields is mainly driven by weather events. In this paper we focus on temperature-based weather events because recent research asserts that temperature changes cause higher crop production uncertainties than changes in precipitation (Lobell and Burke, 2008).

Apart from this empirical contribution, we aim at refining the statistical framework for the analysis of spatial dependence of weather related insurance losses. We employ a combination of daily temperature models and copula techniques which allow a flexible modeling of the joint loss distribution in different regions. Thereby we overcome restrictive assumptions which are imposed by conventional de-correlation analyses. Applying copulas to the analysis of spatial dependence is challenging because of the high dimensionality of the problem. We solve this task by means of a hierarchical Archimedean copula (HAC) (Okhrin, Okhrin and Schmid, 2009; Whelan, 2004; Savu and Trede, 2010). Once the copula function and the marginal distributions of the weather variables have been determined, quantiles of the insurer's total losses can be calculated using Monte Carlo simulations.

The remainder of this article is organized as follows: We start with a brief literature review on the relevance of systemic risk in crop insurance. Next, we describe our model framework: After an introduction of basic definitions we present a statistical model for daily temperatures and introduce the concept of HAC. These models are then applied to Chinese weather data. We present buffer loads for an index-based weather insurance and display the effects of spatial diversification. Moreover, we compare alternative model specifications and check the robustness of the results. The paper ends with a discussion of the feasibility of crop insurance in China.

2 Systemic Weather Risk and its Measurement

A well-known precondition of insurability is that individual risks are independent or the covariance among risks is at least small. This requirement rules out covariate or systemic risk. Cummins and Trainar (2009) illustrate that covariance of insurance claims may increase insurance premium considerably for a given target ruin probability of the (re)insurer, eventually leading to a breakdown in market efficiency. While the independence assumption holds for some types of weather perils, such as hail, it does not hold for other types – at least at a regional

level. Drought risk is an example of a peril that affects most if not all farmers in a region. Therefore, investigation of the dependence structure of unfavorable weather events is important for predicting the development of the agricultural insurance market in China. Miranda and Glauber (1997) argue that the existence of systemic weather risk constitutes the main reason for the failure of private crop insurance markets unless efficient and affordable instruments for transferring this risk are available. However, some authors have questioned the empirical validity of this argument. Wang and Zhang (2003) show by means of a spatial statistics approach that yields of wheat, soybeans and corn in the United States (US) are spatially uncorrelated if the distance between fields is larger than 570 miles. They conclude that only a moderate premium loading is necessary for covering the systemic yield risk if the risk pool is large enough. Goodwin (2001) reports similar findings, but he points out that the correlations between yields fade out slower for extreme years than for normal years.

In view of the relevance of spatial dependence of weather events for crop insurance, it is not surprising that some attempts for quantification have been already made. The usual approach is based on linear correlation coefficients between weather variables or indices which are measured at different locations (weather stations). With these correlation coefficients at hand de-correlation functions can be estimated, depicting correlation of weather variables as a function of the distance between weather stations. Examples of this kind of approach can be found in Woodard and Garcia (2008) and Odening, Mußhoff and Xu (2007). Goodwin (2001) and Wang and Zhang (2003) apply the same technique to US yield data. The use of linear correlation of risks is computationally appealing but has some well- known pitfalls (cf. McNeil, Frey and Embrechts, 2005). In general, linear correlations do not contain all relevant information on the dependence structure of risks. This means that joint distributions with the same correlation coefficient may show different behavior, particularly in their tails. In this paper we use copulas as an alternative to linear correlations since they allow for greater flexibility in modeling the dependence structure of insurance losses in different regions. Copulas became increasingly popular in the last decade and have been applied to various problems in finance and insurance (Embrechts, 2009; Cherubini, Luciano and Vecchiato, 2004; Embrechts, McNeil and Straumann, 1999). Copulas have also been used in the field of climate and meteorological research (e.g. Vrac, Chedin and Diday, 2005; Schoelzel and Friederichs, 2008). Applications in an agricultural context, however, are rare. Vedenov (2008) analyzes the relationship between individual farm yields and area yields and Zhu, Ghosh and Goodwin (2008) investigate the dependence of prices and yields in the context of revenue insurance. The study most similar to ours is by Xu et al. (2010) who derive weather-dependent loss

distributions for different regions in Germany. Unfortunately, their results are plagued by a poor statistical reliability because only 34 annual observations are available for estimating four-dimensional copulas. The data requirements for the estimation of high dimensional dependence structures on the one hand and the insufficient length of annual time series data on the other hand, motivates the use of daily weather models from which appropriate weather indices can be derived.

3 Model Framework

Following Wang and Zhang (2003), we assess the systemic risk inherent to an insurance portfolio via the required buffer fund. The buffer fund (BF) is defined as the Value at Risk (VaR) of the net total losses of the insurer, i.e. the total indemnity payments minus the insurance premium.

$$BF = \inf\left\{l \in \Re : P\left(\sum_{i=1}^{n} w_i \cdot \left(L(X_i) - \pi_i\right) \geq l\right) = 1 - \alpha\right\}, \tag{1}$$

Herein $L(X_i)$ denotes the indemnity payment, which depends on the weather index X_i in region i. The specific form of $L(X_i)$ is introduced below. π_i is the corresponding (fair) insurance premium which is defined as $E[L(X_i)]$. w_i denotes the weight of the ith insurance contract and $1 - \alpha$ is the ruin probability. The buffer fund can be interpreted as the necessary financial reserve held by the insurer to cover extreme indemnity payments and to avoid ruin. Dividing the buffer fund by the number of contracts gives the buffer load (BL), which is the required risk loading above the fair price of the insurance, i.e. $BL = BF/n$. This definition is obviously based on several simplifying assumptions. First, we do not take into account product diversification of the insurer. Second, only a single period is considered and equity reserves that are cumulated in years with premium surpluses are ruled out. Finally, other loading factors capturing administrative costs are ignored.

The risk reducing effect, which can be attained by spatial diversification, is assessed by relating the buffer load for a joint insurance of n regions to the average buffer load for a single region:

$$DE = \frac{BL_n}{\left(\sum_{i=1}^{n} BL_i\right) n^{-1}}, \tag{2}$$

5

where *DE* denotes the diversification effect, BL_n is the buffer load of the whole region and BL_i is the buffer load of location i.

In our analysis two temperature related weather indices are used as an underlying for a hypothetical crop insurance in China. The first index is the "growing degree days" index (GDD), which measures the impact of temperature on the growth and the development of crops during a growing season (The World Bank, 2005).

$$GDD_{i,t} = \sum_{j=\tau_M}^{\tau_O} \max\left(0, T_{i,t,j} - \hat{T}\right), \tag{3}$$

Herein $T_{i,t,j}$ denotes the daily average temperature in degree Celsius recorded at the location i, in year t and day j. τ_M and τ_O stand for the beginning (March 1) and the end (October 31) of the growing season in year t, respectively. The base temperature $\hat{T}$ is the minimum temperature that has to be exceeded before plant growth is stimulated. Though this threshold is plant specific, we assume a constant value of 5°C. Indemnity payments are calculated according to

$$L_{GDD_{i,t}} = \max\left\{0, K_i^{GDD} - GDD_{i,t}\right\} \cdot V. \tag{4}$$

Herein V denotes the tick value which converts physical units into monetary terms. As we do not strive for an optimal contract design in the sense of maximizing the hedging effectiveness, we set $V = 1$. K_i^{GDD} is the strike level. We assume two alternative strike levels, namely the 50 % quantile and the 15 % quantile of the index distribution.

The second index is the "frost index" (FI) suggested by Semenov (2007). It measures the risk of winterkill, i.e. yield losses caused by low temperatures during the winter season. The FI is defined as the total number of days when minimum temperature is below 0°C during winter:

$$FI_{i,t} = \sum_{j=\tau_N}^{\tau_M} I\left\{T_{i,t,j} < 0\right\}, \tag{5}$$

where $T_{i,t,j}$ is the daily average temperature in degrees Celsius in location i, in year t and day j. τ_N and τ_M denote the beginning (November 1) and the end (March 31) of the winter season in year t, respectively. $I\{\cdot\}$ is the indicator function. Indemnities are calculated according to

$$L_{GDD_{i,t}} = \max\left\{0, FI_{i,t} - K_i^{FI}\right\} \cdot V. \tag{6}$$

The 50 % quantile and the 85 % quantile of the index distribution mark the strike levels for this index in the subsequent application.

Evaluation of equation (1) requires knowledge of the joint loss distribution for all insured regions. We decompose the joint distribution into two components: first, the marginal loss distributions for a region i and second, the dependency structure between losses in different regions. As mentioned above, we do not directly estimate marginal distributions for the weather indices. We prefer to model the underlying weather variable (daily average temperature in our case) and to then derive the weather index from it. Thus, we have to specify an appropriate daily temperature model. Copulas are utilized when dealing with the dependence between temperatures in different locations. Due to the fact that daily average temperature is not a *i.i.d* process, the estimation of the dependence structure between locations cannot rest on the raw temperature series, but instead on the standardized *i.i.d* residuals embedded in the temperature dynamics.

Figure 1 visualizes the procedure for the calculation of buffer loads and diversification effects for different regional aggregation levels. In the next section, we describe the time series model for the dynamics of daily average temperature and the copula based model for the determination and estimation of the spatial dependence structure in more detail.

Figure 1: Flow Chart of the Computational Procedure
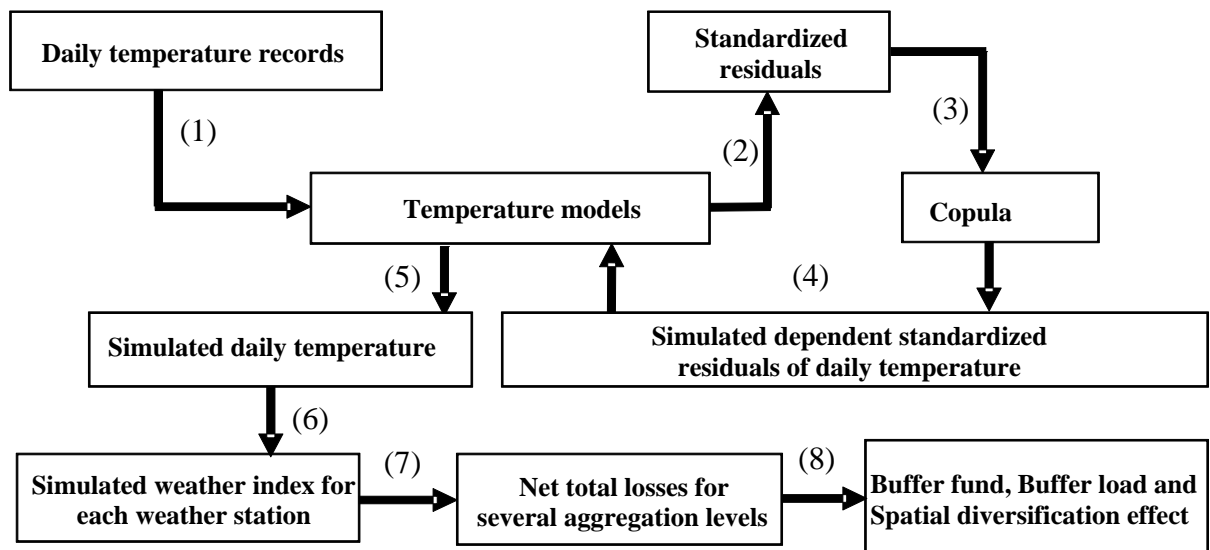
4 Multisite Temperature Modeling

4.1 Temperature Dynamics

Previous research suggests that daily temperature dynamics are characterized by: (a) trend; (b) seasonality; (c) autoregression in the detrended and deseasonalized series; and (d) seasonality in standard deviation. Similar to Campbell and Diebold (2005), we first remove trend and seasonality from daily average temperature and then build an autoregressive (AR) model on this adjusted series. To capture seasonality in the daily temperature data, we used a simple cosine function. For the estimation of the conditional variance, we applied a low-order Fourier series.

We introduce $T_{i,t}$, $\Lambda_{i,t}$ and $\psi_{i,t}$ to denote the daily average temperature ($T_{i,t}$), the seasonal and trend component ($\Lambda_{i,t}$) and the adjusted temperature ($\psi_{i,t}$) in location i at time t, respectively. Using these components, daily average temperature can be described as:

$$T_{i,t} = \Lambda_{i,t} + \psi_{i,t}, \tag{7}$$

$$\Lambda_{i,t} = a_{1,i} + a_{2,i} \cdot t + a_{3,i} \cdot \cos\left(2\pi \frac{t - a_{4,i}}{365}\right), \tag{8}$$

$$\psi_{i,t} = \sum_{j=1}^{J_i} b_{j,i} \cdot \psi_{t-j,i} + \sigma_{i,t} \cdot \varepsilon_{i,t}, \tag{9}$$

with $t = 1,\ldots,T$ and $i = 1,\ldots,n$. The lag order in equation (9) is determined by means of the AIC and the time-varying variance is modeled by:

$$\sigma_{i,t}^2 = d_{1,i} + d_{2,i} \cdot t + \sum_{k=1}^{K_i}\left(d_{3,k,i} \cdot \cos\left(2 \cdot \pi \cdot k \cdot \frac{t}{365}\right) + d_{4,k,i} \cdot \sin\left(2 \cdot \pi \cdot k \cdot \frac{t}{365}\right)\right). \tag{10}$$

The standardized residuals $\varepsilon_{i,t}$ in equation (9) are assumed to be $i.i.d$ $(0,1)$ for a given i.

4.2 Determination of Spatial Dependence Using HAC

Although the above model (equations (7)-(10)) removes seasonality and time varying serial correlations from the daily temperature, the standardized residuals in equation (9) still contain information about spatial correlation (dependence) of the daily average temperature at different

locations i. The joint distribution of the standardized residuals, $\varepsilon = (\varepsilon_1, \ldots, \varepsilon_n)'$, can be expressed as

$$F(\varepsilon) = C\{F_1(\varepsilon_1), \ldots, F_n(\varepsilon_n)\}, \tag{11}$$

where $F_i(\varepsilon_i)$ is the marginal distribution of ε_i and C denotes a copula function describing the dependence structure among $\varepsilon_1, \ldots, \varepsilon_n$. Using the definition $u_i = F_i(\varepsilon_i)$, a copula $C(u_1, \ldots, u_n)$ can be understood as a multivariate distribution function with all margins being uniformly distributed on $[0,1]$.[2] The multivariate density function $f(\varepsilon)$ is then given by

$$f(\varepsilon) = c\{F_1(\varepsilon_1), \ldots, F_n(\varepsilon_n)\} \cdot f_1(\varepsilon_1) \cdot \ldots \cdot f_n(\varepsilon_n) \tag{12}$$

Herein $f_1(\varepsilon_1), \ldots, f_n(\varepsilon_n)$ are marginal densities and $c\{\cdot\}$ is the density function of copula $C(\cdot)$.

In this article we adopt the parametric class of Archimedean copulas, which have been widely used in risk management applications due to their flexibility and tractability (e.g., Embrechts, Lindskog and McNeil, 2003). The general structure of an exchangeable Archimedean copula is given by

$$C(u_1, \ldots, u_n) = \varphi^{-1}\{\varphi(u_1) + \ldots + \varphi(u_n)\}, \tag{13}$$

where φ is the monotone generator function with $\varphi(0) = 1$, $\varphi(\infty) = 0$ and φ^{-1} is its inverse.

The family of Archimedean copulas includes the Clayton, the Gumbel and the Frank copula as special cases exhibiting lower tail dependence, upper tail dependence and tail independence, respectively. Exchangeable Archimedean copulas provide a simple method to estimate and simulate a high-dimensional dependence structure, but rely on restrictive assumptions. The reason is that most multivariate Archimedean copula models present the whole dependence structure with one single copula parameter only, independent of the dimension of the model. Consequently, the substructure of the dependence is hidden. Furthermore, it is implicitly assumed that the order of margins u_i within the copula function is exchangeable. The implied permutation symmetry of the copula represents a very specialized dependence structure, which is not plausible for many applications (cf. McNeil, Frey and Embrechts, 2005).

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[2] For a thorough review of copula theory we refer to Nelsen (2006).

In view of these shortcomings, attempts have been made to develop a more flexible and appropriate Archimedean model for capturing a high-dimensional dependence structure. A powerful approach is the hierarchical Archimedean copula construction (HAC) (cf. Haerdle, Okhrin and Okhrin, 2010). The HAC represents the multivariate dependence structure by a hierarchical order, which starts with a two dimensional copula and ends with a high dimensional copula after several aggregation steps. A HAC embeds two subclasses, namely fully nested Archimedean copulas (FNAC) and partially nested Archimedean copulas (PNAC) which differ in their aggregation scheme. In a FNAC, one dimension is added at each aggregation level (see Figure 2a). More formally, an n-dimensional FNAC can be expressed as (Savu and Trede, 2010):

$$
\begin{aligned}
C(u_1,\ldots,u_n) = \varphi_{n-1}^{-1} \Big\{ \varphi_{n-1} \circ \varphi_{n-2}^{-1} \Big[\ldots \Big(\varphi_2 \circ \varphi_1^{-1} \Big[\varphi_1(u_1) + \varphi_1(u_2) \Big] + \varphi_2(u_3) \Big) \\
+ \ldots + \varphi_{n-2}(u_{n-1}) \Big] + \varphi_{n-1}(u_n) \Big\}
\end{aligned}
\tag{14}
$$

where „$\circ$" denotes the composition operation. The FNAC is therefore characterized by up to $n-1$ copulas composed of $n(n-1)/2$ possible combinations of bivariate marginal distributions (u_i, u_j) with $i \neq j$. Alternatively, a PNAC aggregates copulas of different dimensions (see Figure 2b). A general expression for an n-dimensional PNAC can be found in Okhrin (2010, p.13).

To ensure that the outcome of copula aggregation within a HAC structure results in a proper cumulative distribution function, certain conditions must be fulfilled. To be specific, the composite functions $\varphi_{n-1} \circ \varphi_{n-2}^{-1}$ in equation (14) must have completely monotone derivatives up to order n (McNeil, 2008). Savu and Trede (2010) show that if the degree of dependence diminishes with increasing aggregation level, then the function given in equation (14) is in fact a copula. Unfortunately, the condition of complete monotonicity is difficult to fulfill if different copula types are merged within a single HAC structure. Since the question of feasible combinations of copula types is not yet fully answered, we prefer to use generator functions φ_n from the same copula type for all aggregation levels of the HAC.

In this article we use a mixture of FNAC and PNAC to increase the model's flexibility (Figure 2c). For computational convenience, however, we nest bivariate copulas only at each level of hierarchy. The determination of the structure of the HAC follows the procedure described in Okhrin, Okhrin and Schmid (2009).

Figure 2: Different Types of Hierarchical Archimedean Copulas (HAC)

a)   FNAC   b) PNAC   c) Mixed
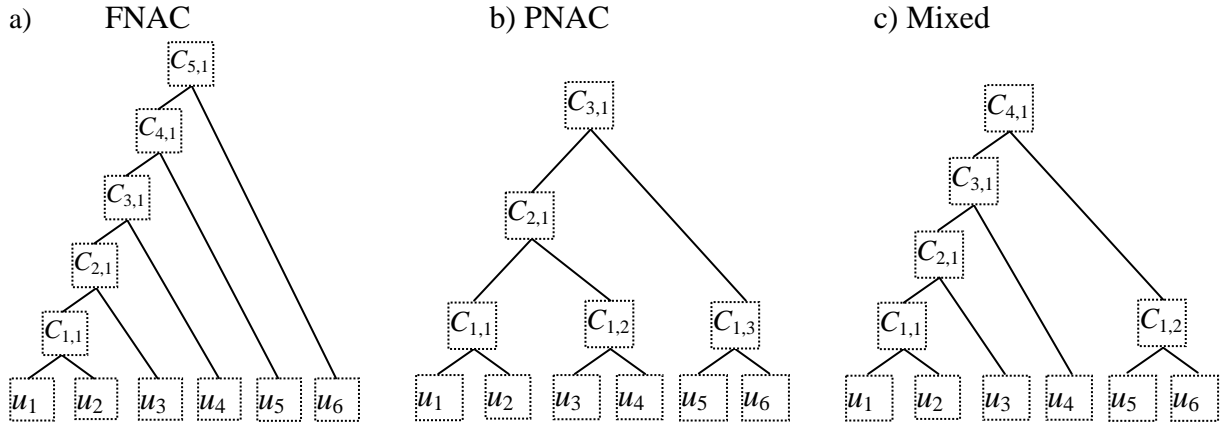
Estimation of the joint distribution of temperature residuals at the different locations is achieved by a multi-stage maximum likelihood procedure (cf. Haerdle, Okhrin and Okhrin, 2010). At first, the marginal distributions of the temperature residuals, ε_i, are estimated either parametrically or non-parametrically. Next, the copula parameters at the first level are estimated with maximum likelihood conditional on the information about the marginal distributions. Thereafter, the copula parameters at the subsequent levels are estimated conditional on the marginals and the copula parameters of the previous levels.

With the estimated HAC structure and marginal distributions at hand, samples of standardized residuals $\varepsilon_{i,t}$ in equation (9) can be generated using Monte Carlo simulation. For the simulation of dependent residuals we apply the iterative algorithm suggested by McNeil (2008), which is based on Laplace transforms. The generated sample of dependent residuals is then plugged into the time series models (equation (7) - equation (10)) to give a n-dimensional vector of simulated daily average temperatures for all locations from which the relevant weather indices are calculated according to equations (3) and (5). The whole procedure is repeated for 500 years yielding a distribution of insurance losses. Finally, the buffer fund and buffer load are derived from the quantiles of these distributions.

5 Analysis of Systemic Weather Risk in China

5.1 Study Area and Data

In our analysis below, we apply the procedure outlined in the previous section to temperature data in China. The investigation region covers seven provinces including Neimenggu, Shanxi, Gansu, Shaanxi, Henan, Hubei and Yunnan with a size of 2.67 Mio. km^2 which is about 28 % of China's entire land area.

Figure 3: Selected Weather Stations in China and Regional Aggregation

a) For GDD

longitude

b) For FI

longitude
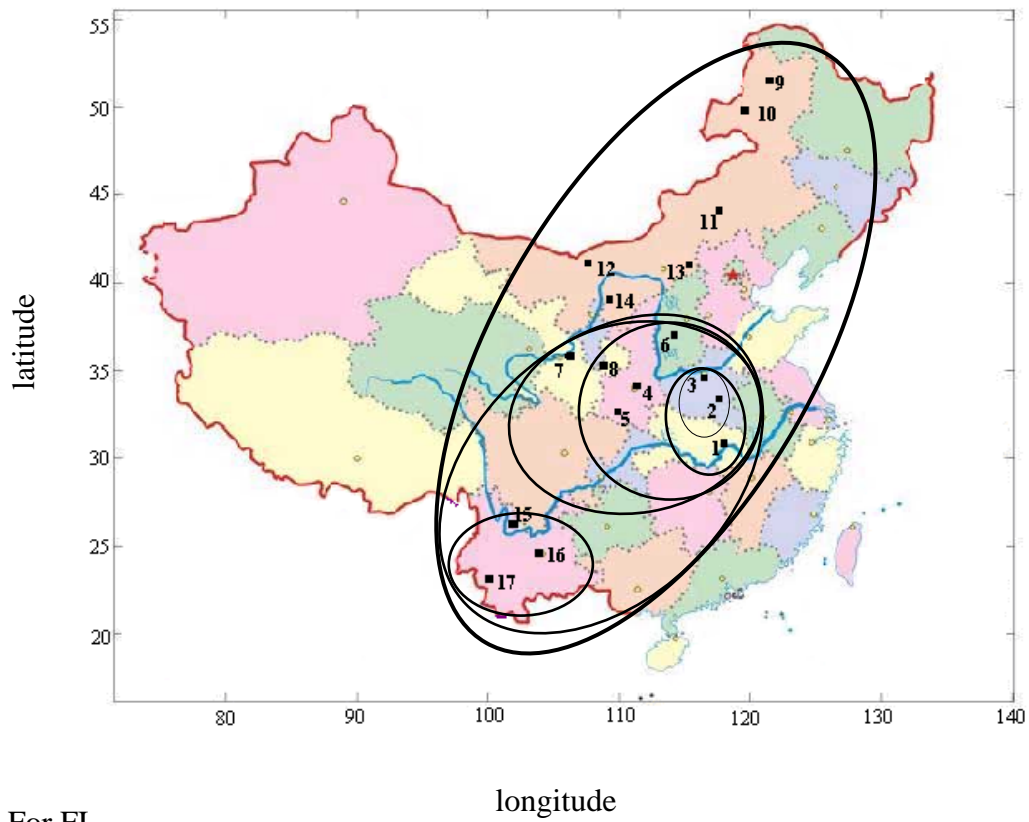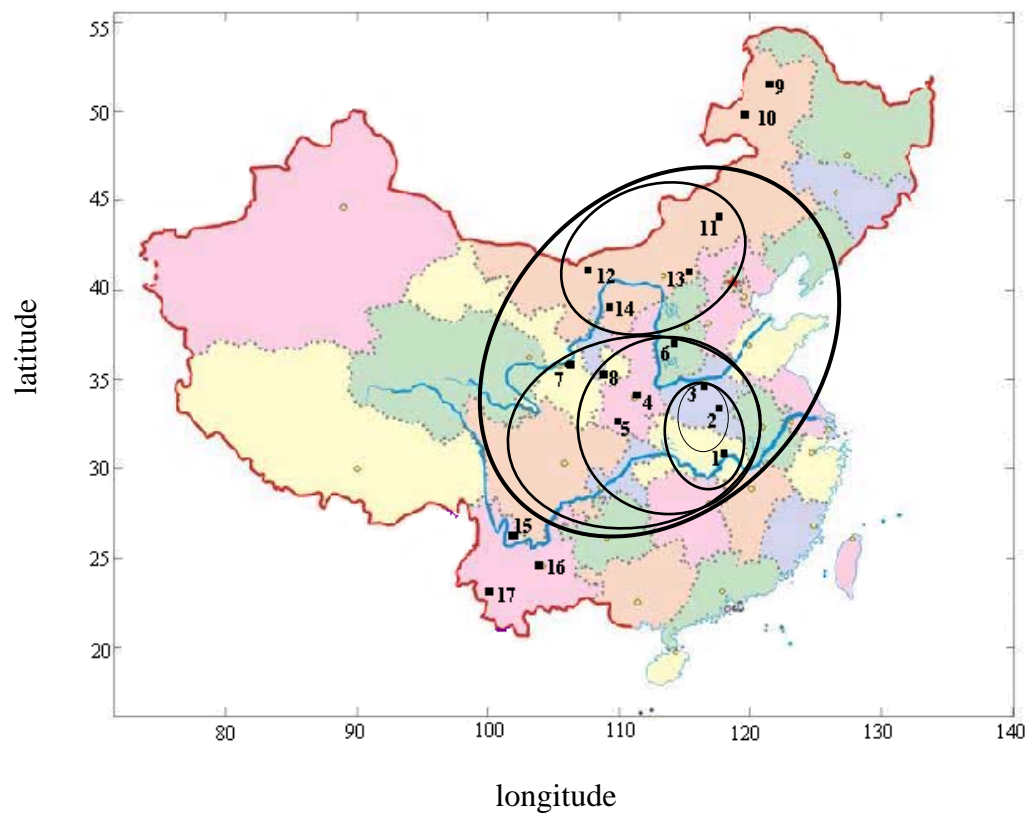
The selection of the study area is based on two criteria: First, agricultural production has high economic relevance and second, pronounced drought and frost damages occur in this part of the country (China Meteorological Administration, 2008; The World Bank, 2007). The study region is divided into 17 homogeneous sub-regions. The differentiation of sub-regions takes into account classifications of ecological zones (e.g., subtropical humid forest zone, temperate mountain zone), temperature zones and the major farming systems. Each of the homogeneous regions is represented by one centrally located weather station. The locations of the selected weather stations are depicted in Figure 3.[3]

Data for this study were provided by the China Meteorological Data Sharing Service System (http://data.cma.gov.cn/). The data set consists of daily observations of average temperature covering the period from January 1st, 1958 to December 31st, 2008. After removing leap years, 18,615 observations are available.

The empirical means and standard deviations of the GDD and the FI are reported in Table 1 for each weather station. Obviously, the 17 sub-regions vary with regard to their temperature characteristics. This heterogeneity is important for the understanding of the effect of an enlargement of the trading area of insurance contracts written on the temperature indices. Moreover, it is apparent that an insurance against frost damages does not make sense for some regions because either no frost occurs or temperatures are typically below zero during the accumulation period.

Using these data we estimate the daily temperature model (equations (7)-(10)) for each weather station. Equations (8) and (10) are estimated by least squares, while equation (9) is estimated with quasi-maximum likelihood. The order of the Fourier series in equation (9) is up to order 5 according to the AIC for all weather stations.[4] After removing the estimated trend and seasonality from the temperature data, we conducted standard goodness-of-fit tests for the marginal distributions of the residuals. In most cases, the Weibull and the logistic distribution offer the best fit. The non-normality of temperatures, which is also confirmed by other studies (e.g. Schoelzel and Friederichs, 2008), questions the use of linear correlation analysis and justifies the copula approach which we pursue here.

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[3] We select from international weather stations only, which are registered at the World Meteorological Organization (WMO), since these stations provide the most reliable data. Weather stations located at high elevations have been excluded.

[4] The parameter estimates of the temperature model are available upon request.

Table 1: Descriptive Statistics of Temperature Indices

Weather Station	Mean		Standard Deviation	
	GDD	FI	GDD	FI
1	4114.98	6.26	198.13	6.07
2	3740.56	19.92	148.25	10.29
3	3700.36	30.76	146.95	12.23
4	3517.92	32.22	186.12	12.32
5	3498.83	5.86	144.03	5.18
6	2897.29	75.60	140.68	11.64
7	2623.34	87.44	172.30	12.07
8	2339.84	86.14	137.39	12.65
9	1103.83	150.54	97.58	1.03
10	1648.30	148.86	143.36	2.05
11	1950.79	141.54	150.38	3.92
12	2222.72	131.80	135.10	7.05
13	2373.50	120.70	177.23	8.76
14	2353.13	117.68	141.53	9.24
15	2557.45	0.20	103.70	0.64
16	3113.99	0.26	156.99	0.60
17	3670.46	00.00	105.20	00.00

5.2 Spatial Dependence of Temperatures and Regional Aggregation

As mentioned above, the estimation of the HAC is accomplished in two stages. In the first stage, the whole hierarchical structure – including the substructure – is determined. Given this structure, the copula parameters are estimated in the second stage assuming the same type of Archimedean copula for all hierarchy levels. Two alternative Archimedean copula types are considered, namely the Gumbel copula and the rotated Gumbel copula. The Gumbel copula and rotated Gumbel copula represent upper and lower tail dependence, respectively. The rotated Gumbel copula is used as a proxy for the Clayton copula, which is much more difficult to handle from a computational viewpoint. In addition, we estimate a 17-dimensional Gaussian copula as a benchmark for the HAC, which exhibits tail independence of the joint temperature distribution. The parameters of the Gaussian copula, i.e. the matrix of correlation coefficients, are presented in Table A1 in the appendix.

Our modeling approach implicitly assumes that the spatial dependence structure of the underlying temperature variables is constant over time. Inspection of linear correlation coefficients between weather stations in the course of a year casts doubt on the validity of this assumption. It is, in principle, possible to estimate time-varying copula parameters (e.g., Giacomini, Haerdle and Spokoiny, 2009), but the computational procedure is burdensome. To address possible changes in the dependence structure we divide the temperature data for one year into four seasons (with three month each) and estimate specific copula parameters for each season. Table A2 depicts the estimated seasonal parameters for the Gumbel HAC.[5] Afterwards the marginal distributions of the temperature standard residuals are estimated non-parametrically, i.e. we estimate the empirical distributions. Simulation from these distributions is carried out with a bootstrap procedure.

As we are interested in the effect of enlarging the trading area on the systemic risk of weather-related insurance, an aggregation scheme for the 17 regions in the study area must be specified. Aggregation could be accomplished by means of the distance between regions or with regard to the correlations of temperatures or insurance losses; however, in our analysis we utilize the information on the dependence structure that is provided by the HAC.[6] This means that starting arbitrarily with region 2, we form a cluster consisting of the regions 2 and 3. The number of regions is then increased step by step to a countrywide insurance portfolio including all 17 locations. The result of this aggregation procedure is presented in Table 2 and also visualized by elliptical circles in Figure 3. It turns out that the distance between weather stations plays a role for the aggregation sequence, but that the order of regional clustering is not a simple linear function of distance. This finding questions the results of simple uni-directional de-correlation analyses.

Table 2: Aggregation of Insurance Regions

Aggregation level		0	1	2	3	4	5	6
Insured area for	GDD	2	2, 3	1-3	1-6, 8	1-8	1-8, 15-17	1-17
	FI	2	2, 3	1-3	1-6, 8	1-8	1-8, 11-14	---

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[5] Note that rotated Gumbel HAC has the same hierarchical structure and identical copula parameter as the Gumbel HAC. The only difference is that the simulated values u_i are replaced by $1 - u_i$.

[6] The aggregation scheme is based on the HAC results for the entire, non-seasonal data set.

5.3 Risk Pooling through Regional Aggregation

Figure 4 presents the buffer load of both GDD and FI for different aggregation levels. The buffer load is derived from the 5 % quantile of the distribution of total net losses. Indemnity payments are calculated for two alternative strike levels, namely the 50 % and the 15 % quantile for the GDD index and the 50 % and 85 % for the frost index.

Figure 4: Buffer Loads for Different Regional Aggregation Levels

a) GDD
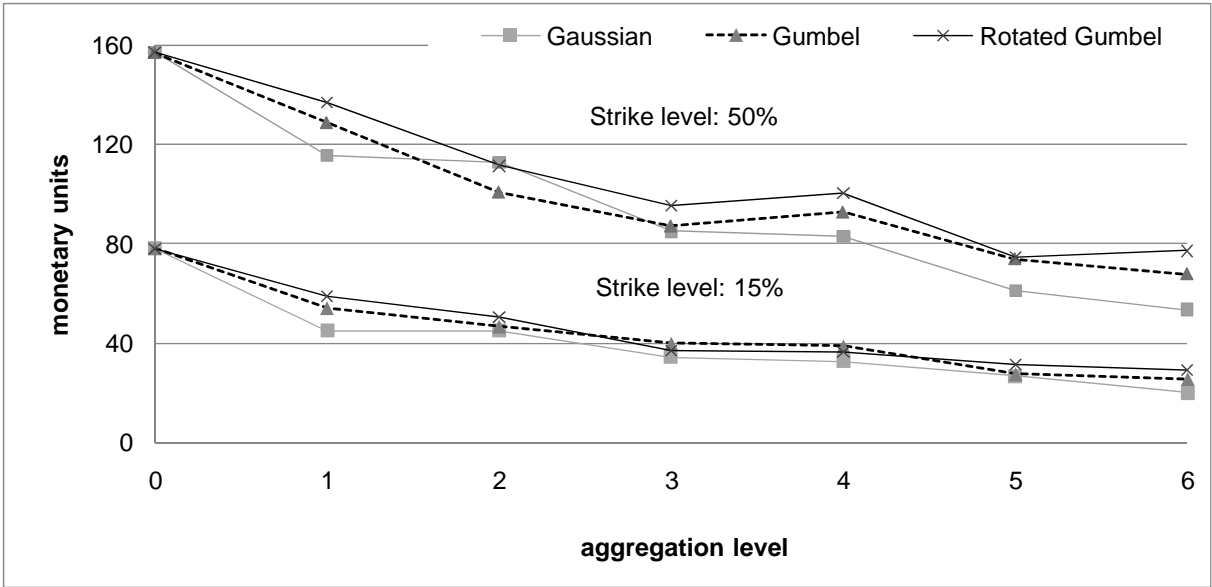
b) FI
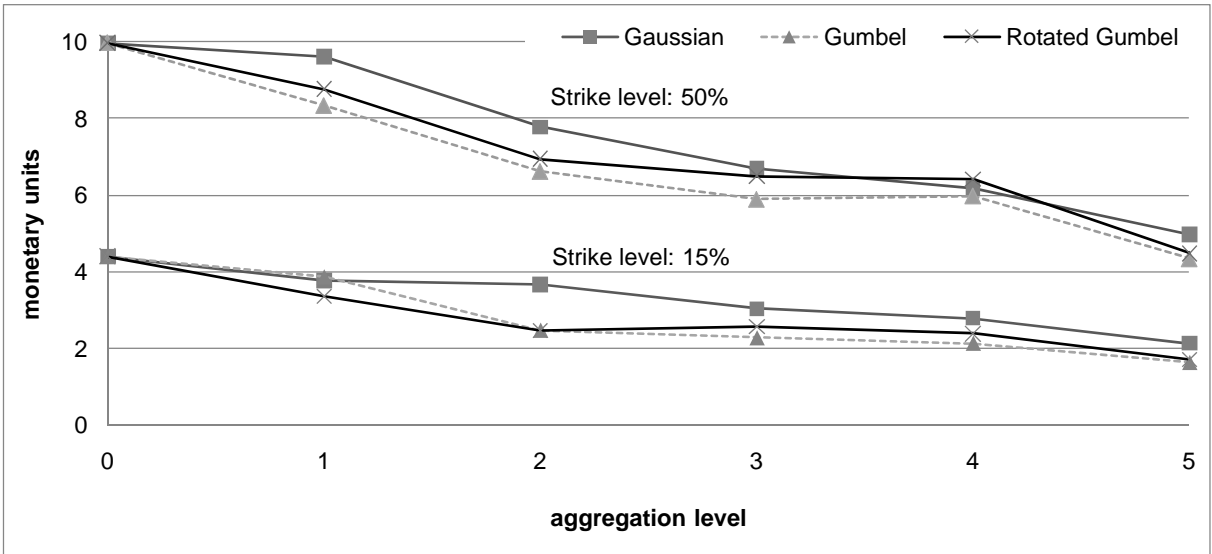
Though the regions differ in size and potential insurance demand, equal weights are assigned to them in the hypothetical insurance portfolio. Obviously, the buffer load of the temperature-based insurance contracts can be reduced considerably through the aggregation of

regions, i.e. an enlargement of the trading area. At the lowest aggregation level, the buffer load of the GDD contract with a strike of 50 % varies between 115.63 and 136.88 monetary units depending on the assumed copula model. At the highest aggregation level, which includes all regions, the buffer load is only half as high and varies between 53.46 and 77.14 monetary units. This corresponds to a loading factor between 2.14 and 2.65 in relation to the actuarially fair premium.

Figure 4a) also reveals that the buffer load does not monotonously decrease with an increasing aggregation level. This finding can be explained by the heterogeneity of the regions with regard to their weather risk exposure, meaning that losses are not identically distributed. The buffer load is considerable smaller in absolute terms for a contract with a strike level of 15 % compared to a strike level of 50 %. As before, there is a significant decline; however, the loading factor is higher (approximately 3.12 to 4.16 for the entire trading). This indicates that the tails of GDD distributions show a higher dependence than values around the means of the distribution.

Table 3 summarizes the diversification effect that results from the enlargement of the insured areas. The figures measure the buffer load of a joint insurance of all 17 regions relative to a situation where all regions are insured separately. Recall that in the case of normal *i.i.d* losses, the buffer load would decrease by a factor $1/\sqrt{17} = 0.24$. The fact that the reduction is smaller for the analyzed insurance contract proves that systemic weather risk is present. Nevertheless, spatial diversification is rather effective in the case of the GDD.

Similar findings apply to the insurance contract based on the frost index (FI). Figure 4 b) shows that the buffer load is a declining function of the aggregation level for the FI. Table 3 reports that the diversification effect has a similar size as in the case of the GDD. On the other hand, the required loading factor of the FI contract is higher: it amounts to approximately 2.65 to 3.08 (4.49 to 4.89) for a strike level of 50 % (85 %).

It is also worthwhile to compare the outcome of the different copula models. Figure 4 displays considerable differences for the buffer loads. For example, at the highest aggregation level the buffer load for the GDD contract with a strike level of 50 % is 44 % higher according to the rotated Gumbel copula than according to the Gaussian copula. The results of the Gumbel copula fall between these values. Similar differences can be found for the diversification effect. These differences are not surprising if one recalls the different dependence structures that are implied by these copula types. The results for the FI contract are less pronounced.

Table 3: Fair Prices, Buffer Loads and Diversification Effects (Entire Insurance Area)

Type of Copula	Gaussian	Gumbel	Rotated-Gumbel
GDD Strike Level 50 %			
Fair Price	46.96	46.87	46.65
Buffer Load	53.46	67.77	77.14
Loading factor	2.14	2.45	2.65
Diversification Effect	0.36	0.44	0.50
GDD Strike Level 15 %			
Fair Price	9.42	9.26	9.21
Buffer Load	19.95	25.66	29.06
Loading factor	3.12	3.77	4.16
Diversification Effect	0.33	0.41	0.40
FI Strike Level 50 %			
Fair Price	3.02	2.09	2.16
Buffer Load	4.97	4.34	4.48
Loading factor	2.65	3.08	3.07
Diversification Effect	0.50	0.48	0.53
FI Strike Level 85 %			
Fair Price	0.61	0.43	0.44
Buffer Load	2.13	1.63	1.71
Loading factor	4.49	4.79	4.89
Diversification Effect	0.52	0.44	0.47

Finally, we analyze the sensitivity of the results with regard to the data set used for the estimation of the systemic risk and the according risk premium. For this purpose, we estimate our models with a moving data window that consists of 20 years of daily temperature data so that we have a total of 32 subsamples. The resulting buffer loads on the highest aggregation level are depicted in Figure 5.

No clear trend can be discovered in the buffer loads, neither for the GDD nor for the FI, which means that the conjectured increase of weather risk is not reflected in the risk premium for this hypothetical insurance. On the other hand, there are considerable changes in the buffer load from year to year which indicate that the premium calculation heavily depends on the data. Again one can find clear differences in the result of the three alternative copula models. In some years these differences amount up to 31 % between the Gaussian copula and the rotated-Gumbel copula for the GDD and up to 33 % between the rotated-Gumbel copula and the Gumbel copula for the FI. Moreover, it is striking that the annual changes of the buffer load in some cases have different signs for the three models.

Figure 5: Moving Window Estimation of Buffer Loads

a) GDD (Aggregation Level 6)
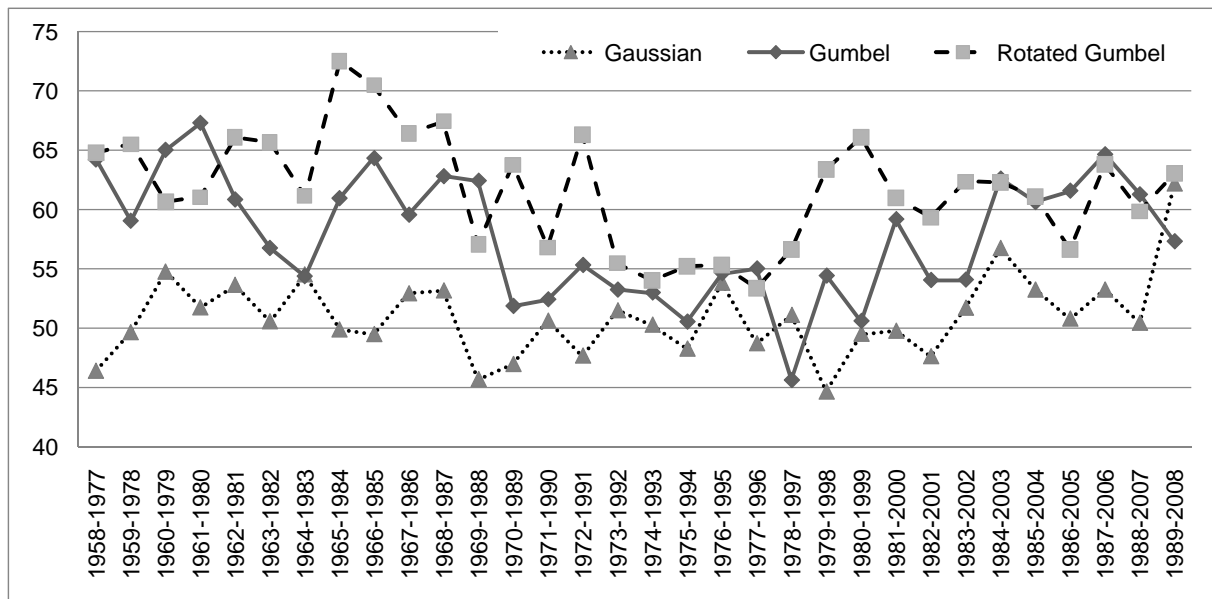
b) FI (Aggregation Level 5)
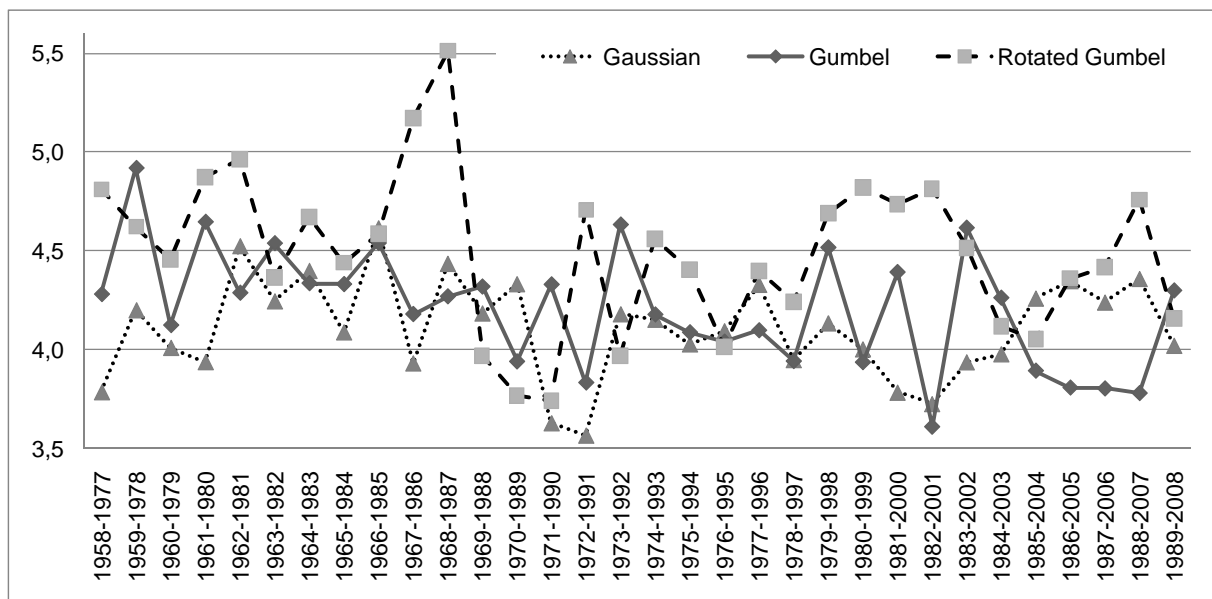
6 Summary and Conclusions

This article investigates the systemic risk inherent to index-based insurance for 17 agricultural production regions in China. The application is motivated by the fact that agricultural insurance companies in China are currently developing insurance products which protect farmers against multiple perils, including drought risk. As weather constitutes the major source of yield risk, we define two temperature indices and calculate the buffer load (risk premium) for insurance

contracts written on these indices. We are particularly interested in the possibility of spatial diversification, i.e. in the decline of the risk premium when the trading area for the insurance increases. Our results are relevant for insurers and reinsurers intending to launch temperature-based insurance products, as well as for insurance regulators when determining the necessary financial reserves to prevent illiquidity. Since weather variables (as well as yields) are characterized by non-normality and tail dependence of joint distributions, we apply a copula based approach instead of a conventional de-correlation analysis. The problem of multidimensionality is overcome by a hierarchical Archimedean copula construction (HAC). Our results reveal a significant spatial diversification effect. Buffer loads decline by more than 50 % if the losses are aggregated over several provinces. The structure of the HAC reveals that stochastic dependence of indemnities depends on the distance between regions, but not in a simple manner. Despite the diversification effect, the loading factors range between 2.14 and 4.16 even at the highest aggregation level. Such risk premiums are relatively high compared to insurance for other agricultural risks, such as hail and it is questionable if Chinese farmers are willing to pay these prices for temperature-based insurance. Our results are consistent with the findings of Miranda and Glauber (1997) who report that crop insurance companies in the US face portfolio risks about 30 times larger than if indemnities were independent.

Our results should be interpreted with care, as they rely on several assumptions that have an influence on the level of the buffer load. First, we did not take into account product diversification of the insurer. Second, only a single period was considered and equity reserves cumulated in years with premium surpluses have been ignored. Third, the buffer load can be controlled by the choice of the strike level for the indemnity payments. It can be expected that the dependence of insurance payoffs at different locations becomes smaller if the strike level is reduced. Finally, regional differences in soil quality, for example, may lead to differences in yields even if weather conditions are similar.

In conclusion, our findings may explain the reluctance of insurance companies to offer crop insurance in many countries in the absence of subsidies. Global reinsurance or transferring weather risk to capital markets by means of weather bonds could alleviate this problem (e.g. Barieu and El Karoui, 2002; Vedenov, Epperson and Barnett, 2006).

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Table A1: Correlation Matrix of Temperature Residuals

Weather station	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	1																
2	0.58	1															
3	0.43	0.78	1														
4	0.48	0.55	0.58	1													
5	0.38	0.28	0.27	0.57	1												
6	0.36	0.57	0.66	0.57	0.27	1											
7	0.29	0.22	0.19	0.31	0.30	0.24	1										
8	0.42	0.45	0.42	0.60	0.44	0.52	0.57	1									
9	0.10	0.16	0.20	0.10	0.05	0.19	0.10	0.12	1								
10	0.05	0.07	0.12	0.04	0.03	0.13	0.12	0.10	0.71	1							
11	0.06	0.09	0.16	0.05	0.04	0.25	0.23	0.19	0.35	0.53	1						
12	0.18	0.18	0.21	0.14	0.09	0.32	0.38	0.34	0.15	0.21	0.50	1					
13	0.25	0.28	0.31	0.27	0.18	0.46	0.38	0.41	0.17	0.20	0.47	0.73	1				
14	0.20	0.23	0.24	0.17	0.12	0.38	0.46	0.45	0.12	0.18	0.45	0.75	0.64	1			
15	0.13	0.08	0.08	0.14	0.17	0.08	0.13	0.14	0.00	-0.02	-0.02	0.02	0.05	0.03	1		
16	0.14	0.07	0.07	0.15	0.17	0.10	0.17	0.20	0.02	0.02	0.05	0.08	0.11	0.10	0.38	1	
17	-0.01	-0.02	-0.01	0.02	0.01	-0.01	0.03	0.02	-0.02	-0.03	-0.01	-0.01	-0.03	-0.03	0.26	0.37	1

Table A2: Parameter Estimates for the Gumbel HAC

Parameter	Estimation	Dimension	Combination	Parameter	Estimation	Dimension	Combination	Parameter	Estimation	Dimension	Combination	Parameter	Estimation	Dimension	Combination	Parameter	Estimation	Dimension	Combination
Whole Sample Jan.-Dec.				First Season Jan.-Mar.				Second Season Apr.-Jun.				Third Season Jul.-Sep.				Fourth Season Oct.-Dec.			
$C_{1,1}$	2.11		u_2, u_3	$C_{1,1}$	2.35		u_2, u_3	$C_{1,1}$	2.20		u_2, u_3	$C_{1,1}$	1.42		u_{15}, u_{16}	$C_{1,1}$	2.11		u_2, u_3
$C_{1,2}$	1.68		u_4, u_5	$C_{1,2}$	2.22	2	u_{12}, u_{14}	$C_{1,2}$	1.76		u_4, u_5	$C_{1,2}$	1.83		u_2, u_3	$C_{1,2}$	1.57		u_7, u_8
$C_{1,3}$	1.43	2	u_{15}, u_{16}	$C_{1,3}$	2.05		u_9, u_{10}	$C_{1,3}$	2.05	2	u_{12}, u_{13}	$C_{1,3}$	1.65	2	u_4, u_5	$C_{1,3}$	2.10	2	u_{12}, u_{14}
$C_{1,4}$	1.98		u_9, u_{10}	$C_{1,4}$	1.35		u_{16}, u_{17}	$C_{1,4}$	2.11		u_9, u_{10}	$C_{1,4}$	1.63		u_{12}, u_{14}	$C_{1,4}$	2.11		u_9, u_{10}
$C_{1,5}$	1.94		u_{12}, u_{14}	$C_{2,1}$	1.79		$C_{1,1}$, u_6	$C_{1,5}$	1.52		u_{15}, u_{16}	$C_{1,5}$	1.70		u_9, u_{10}	$C_{1,5}$	1.45		u_{15}, u_{16}
$C_{2,1}$	1.13		$C_{1,1}$, u_1	$C_{2,2}$	2.09	3	$C_{1,2}$, u_{13}	$C_{2,1}$	1.70		$C_{1,1}$, u_6	$C_{2,1}$	1.38		$C_{1,1}$, u_{17}	$C_{2,1}$	1.72		$C_{1,1}$, u_6
$C_{2,2}$	1.59	3	$C_{1,2}$, u_8	$C_{2,3}$	1.35		$C_{1,4}$, u_{15}	$C_{2,2}$	1.73	3	$C_{1,2}$, u_8	$C_{2,2}$	1.38		$C_{1,2}$, u_6	$C_{2,2}$	1.91	3	$C_{1,3}$, u_{13}
$C_{2,3}$	1.32		$C_{1,3}$, u_{17}	$C_{3,1}$	1.78	4	$C_{2,1}$, u_4	$C_{2,3}$	2.05		$C_{1,3}$, u_{14}	$C_{2,3}$	1.44	3	$C_{1,3}$, u_8	$C_{2,3}$	1.60		$C_{1,4}$, u_{11}
$C_{2,4}$	1.92		$C_{1,5}$, u_{13}	$C_{3,2}$	1.56		$C_{2,2}$, u_{11}	$C_{2,4}$	1.32		$C_{1,5}$, u_{17}	$C_{2,4}$	1.63		$C_{1,4}$, u_{13}	$C_{2,4}$	1.29		$C_{1,5}$, u_{17}
$C_{3,1}$	1.29	4	$C_{2,2}$, u_6	$C_{4,1}$	1.65	5	$C_{3,1}$, u_8	$C_{3,1}$	1.56	6	$C_{2,1}$, $C_{2,2}$	$C_{2,5}$	1.29		$C_{1,5}$, u_{11}	$C_{3,1}$	1.72	4	$C_{2,1}$, u_4
$C_{3,2}$	1.22		$C_{2,4}$, u_{11}	$C_{4,2}$	1.39		$C_{3,2}$, u_7	$C_{3,2}$	1.48	4	$C_{2,3}$, u_{11}	$C_{3,1}$	1.07	4	$C_{2,1}$, u_1	$C_{3,2}$	1.54	5	$C_{1,2}$, $C_{2,2}$
$C_{4,1}$	1.16	7	$C_{2,1}$, $C_{3,1}$	$C_{5,1}$	1.56	6	$C_{4,1}$, u_1	$C_{4,1}$	1.36	7	$C_{3,1}$, u_7	$C_{3,2}$	1.36		$C_{2,4}$, u_7	$C_{4,1}$	1.49		$C_{3,1}$, u_1
$C_{4,2}$	1.19	6	$C_{1,4}$, $C_{3,2}$	$C_{6,1}$	1.44	7	$C_{5,1}$, u_5	$C_{5,1}$	1.28	11	$C_{4,1}$, $C_{3,2}$	$C_{4,1}$	1.37	6	$C_{2,2}$, $C_{2,3}$	$C_{5,1}$	1.42	6	$C_{4,1}$, u_5
$C_{5,1}$	1.08	8	$C_{4,1}$, u_7	$C_{7,1}$	1.39	12	$C_{4,2}$ $C_{6,1}$	$C_{6,1}$	1.19	12	$C_{5,1}$, u_1	$C_{5,1}$	1.26	10	$C_{4,1}$, $C_{3,2}$	$C_{6,1}$	1.42	11	$C_{5,1}$, $C_{3,2}$
$C_{6,1}$	1.05	11	$C_{5,1}$, $C_{2,3}$	$C_{8,1}$	1.23	14	$C_{1,3}$, $C_{7,1}$	$C_{7,1}$	1.14	14	$C_{6,1}$, $C_{1,4}$	$C_{6,1}$	1.13	13	$C_{5,1}$, $C_{2,5}$	$C_{7,1}$	1.29	14	$C_{6,1}$, $C_{2,3}$
$C_{7,1}$	1.04	17	$C_{6,1}$, $C_{4,2}$	$C_{9,1}$	1.08	17	$C_{2,3}$, $C_{8,1}$	$C_{8,1}$	1.00	17	$C_{7,1}$, $C_{2,4}$	$C_{7,1}$	1.03	17	$C_{6,1}$, $C_{3,1}$	$C_{8,1}$	1.13	17	$C_{7,1}$, $C_{2,4}$

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