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Highlights

- This study analyses whether spatial diversification reduces systemic risk.
- Daily temperature and rainfall models are used to derive greater data samples.
- Systemic risk is assessed through the Buffer Load, as measured by the Expected Shortfall, and the diversification effect.
- Broadening the trading area generates significant diversification effects.
- Rainfall insurance is a less-risky alternative as compared to temperature policies.

Abstract

This study assesses how effective spatial diversification is in reducing the systemic risk implied by a market for weather index-based insurance in Spain and compares rainfall- and temperature-based policies in terms of systemic risk. Based on historical weather data, daily models which rely on the multivariate normal distribution are applied to derive greater samples. The results show that the Buffer Load, as measured by the Expected Shortfall, decreases up to 67% as the level of aggregation increases. This suggests that the trading area should not be focused on a specific county, but on Spain as a whole. Considering the highest aggregation degree, it is also shown that the diversification effect is significant, of up to 0.35. Finally, it is noted that rainfall insurance is a less-risky alternative as compared to temperature-geared contracts, as it implies lower losses and prices and stronger risk pooling effectiveness. Therefore, we recommend the inclusion of this type of policies in the insurance companies' portfolio. Finally, although this study focuses on a specific country, the proposed methodology can be easily extrapolated to other geographical areas.

Keywords: weather index-based insurance; spatial diversification; systemic weather risk; risk pooling effectiveness; multivariate normal distribution.

JEL Codes: C15, G22, Q54

1. Introduction

Climate change is increasingly leading to more frequent and intense extreme weather events. This raising weather variability will affect the agricultural industry most probably, entailing negative consequences for both the yield amount and quality (Mäkinen et al., 2018). This may become a challenge to global food security and supply (Semenov and Shewry, 2011; Porter et al., 2014; Trnk et al., 2014; Asseng et al., 2015; Ray et al., 2015).

Although the impact of climate change varies across countries and regions, especially negative effects are expected for the major food and feed crops both in tropical and temperate areas, such as Southern Europe (Porter et al., 2014; Mäkinen et al., 2018). In fact, it has been pointed out that European farms have slightly higher sensitivity to global warming than American farms, and, as reported in Van Passel, Massetti, and Mendelsohn (2016), those located in Southern Europe are projected to suffer losses ranging from 5% to 9% per Celsius degree.

The current context emphasizes, thus, the urge of implementing measures to protect farms' revenues, particularly in those regions which are more sensitive to the effects of climate change (Rufat et al., 2015). As a consequence, several alternatives to mitigate meteorological risk exposure have been suggested and eventually implemented in agriculture and other weather-sensitive industries. These measures can be of operational or financial nature (Allayannis, Ihrig, and Weston, 2001). The first group comprises those hedging strategies that imply a change in business operations, such as the acquisition of new technologies as well as geographical and product diversification. For their part, the financial alternatives, represented by loss-based insurance and weather index-based insurance or weather derivatives, are those that aim to transfer risk to the market or insurance companies. This last type of measures are less capital-demanding and their implementation can be easily reversed (Tang and Jang, 2012).

Among the financial alternatives, the popular and widely implemented loss-based modality stands as the preferred choice while the most recent option of weather index-based insurance remains as the great unknown, despite its advantages. This paper focuses on this last instrument, which insures the cause or event instead of the effect. By doing so, it overcomes two of the most relevant drawbacks inherent to the loss-based modality: adverse selection and moral hazard. Furthermore, this hedging alternative also results more affordable, as payoffs are derived from objective criteria (Skees and Reed, 1986; Quiggin, Karagiannis, and Stanton, 1993; Smith and Goodwin, 1996; Coble et al., 1997; Hess, Richter, and Stoppa, 2002; Turvey and Kong, 2010). Given the welfare improvements that it poses, this tool shows a high potential to benefit the agricultural sector and many other weather-sensitive industries (Ye et al., 2017). However, its operational feasibility still needs to be further studied. In fact, the analysis of different issues related to this topic, such as the factors influencing farmers' willingness to pay (Liu et al., 2019; Senapati, 2020), has proven to be crucial to ensure a correct insurance design and to spread the implementation of this tool.

This paper approaches one of the main challenges refraining the supply of this hedging alternative: systemic risk. This source of uncertainty arises from the fact that effective insurability requires the presence of uncorrelated risks that occur with high frequency (Woodard et al., 2012). However, this requirement may be sometimes violated concerning index insurance, as the geographical dependence of the underlying weather measures can cause correlation in losses and lead to a large number of concurrent insurance claims (Glauber, 2004). In fact, several authors have shown that correlation is sometimes high and significant, especially at regional level, which cannot be afforded by private insurers. To avoid public intervention and the settlement of government subsidies, it is essential that insurance companies allocate a buffer fund, so that bankruptcy is avoided in the face of systemic risk (Miranda and Glauber, 1997; Mahul, 1999; Skees and Barnett, 1999; Duncan and Myers, 2000; Odening and Shen, 2014, Nguyen-Huy et al., 2019).

As noted in Xu et al. (2010) and Odening and Shen (2014), insurers may mitigate and diversify the degree of systemic weather risk by broadening the trading territory. For example, excessive temperatures occurring within a small area might be highly correlated and decrease or even disappear at a broader scale. We focus on this topic in this article. Concretely, the objective of this study is twofold: 1) discerning whether an increase in the trading area can reduce systemic risk and, being this the case, to what extent; and 2) comparing the degree of systemic risk implied by temperature- and rainfall-based policies. These issues are assessed for Spain, given that this country, jointly with others in Southern Europe, is expected to be highly affected by climate change and, therefore, to experience more intense and frequent extreme weather events (Porter et al., 2014; Van Passel, Massetti, and Mendelsohn, 2016). Moreover, the agricultural industry, which is very sensitive to weather conditions, has a high weight in the productive structure of this country.

To address the main goals of this study, we suggest the use of the multivariate normal distribution, which is applied to quantify dependence between weather states at different locations. Although this method is widely accepted in the meteorological literature, it has not been previously used to assess systemic risk in the context of weather-index insurance. This is a novel contribution of our research, which opens the path to its application by both industry practitioners and researchers. In fact, this method is significantly superior to the frequently used linear correlations, given that it captures non-linear dependencies. Furthermore, it shares some of the advantages usually highlighted for copulas, as it defines the joint distribution considering both the variables' marginal distribution and their correlation matrix. However, it is mathematically tractable, more straightforward, easier to understand, and less computationally demanding than multivariate copulas, and this reinforces the benefits of its application. One of the main pitfalls that may refrain the use of the multivariate normal distribution is that weather indices are not always normally distributed. However, in this study we overcome this drawback by employing the widely-applied and well-known daily rainfall model proposed by Wilks (1998) and latter refined by Mhanna and Bauwens (2011), whose steps are explained in more detail in Section 3.3.2. The model assumes that rainfall follows a Gamma distribution, given that this meteorological variable is bounded on the left by zero and thus, it is non-normally distributed (Shah, 2017). In fact, the Gamma distribution has been widely suggested in literature to capture rainfall patterns (Cao et al., 2004;

Leobacher and Ngare, 2011; Shah, 2017), given that it starts at the origin and has flexible shape (Forbes et al. 2011). The basic idea of the model, from which its main advantage is derived, is to assume that the needed correlations of random numbers are equal to the Gamma correlations between the rainfall occurrence series. The stochastic simulation is forced by a random number generator that generates correlated normal variates and then transforms them individually to get uniform marginal distributions. This multi-site rainfall model is able to reflect spatial characteristics efficiently. Mhanna and Bauwens (2011) provide the 'step by step' procedure proposed by Wilks (1998) and suggest some improvements to the previous model. Concerning temperature, we combine the broadly used technique initially suggested by Alaton, Djehiche, and Stillberger (2002) with some of the steps proposed by Mhanna and Bauwens (2011).

Another original scholarly contribution of this article is the assessment and comparison of both temperature- and rainfall-based policies. This has been done previously only by Xu et al. (2010). However, the statistical reliability of this study was limited, as these authors did not generate random data. Instead, they based their results and conclusions on a small real sample. We overcome this limitation by comparing the degree of systemic risk implied by both weather variables using a methodology that allows the generation of random data. It is expected that correlation in terms of precipitation is lower and, therefore, that this variable has greater systemic risk reducing potential as compared to temperature. Being such the case, the supply of rainfall-based policies may contribute significantly to the mitigation of the degree of risk faced by insurers. Of course, it is worth noting that the methodology followed in this research can be extrapolated to other geographical areas easily.

It should be noted that, although the importance of rainfall index insurance has increased over the last years, especially in rural areas, it is still undersupplied by insurance firms. These companies are often reluctant to the use of this insurance modality due to the degree of systemic risk. Thus, one of the most relevant remaining challenges to boost the supply of this insurance typology is deciding the size of the insured area, so that insurance firms can face an affordable degree of systemic risk. This study provides a methodology which helps insurance companies in this regard and contributes to the decision on their trading area. This may not only have positive effects for private insurers, but might also have important public policy implications. In fact, the methodology proposed in this study can help avoid the need of public intervention.

The rest of the article is organized as follows. The second section reviews the most relevant studies approaching geographical diversification as a mean to reduce systemic risk in the context of index insurance. Next, the third section introduces the materials and methods used to assess the degree of systemic risk and the pooling efficiency as well as those applied to generate bigger samples of meteorological data. The fourth section shows and discusses the main results reached. Finally, the fifth section ends up with some concluding remarks.

2. Literature review

As previously mentioned in Section 1, agriculture and thus, crop insurance, are highly affected by systemic risk. This type of risk arises from the spatial positive correlations usually found among crop yields, which are caused by widespread weather events (Feng and Hayes, 2016). As a result, several authors have highlighted that public intervention may be needed for crop insurance, given that the degree of systemic risk derived from natural disasters, such as droughts, floods, and other weather-related events (Miranda and González Vega, 2010), might be too high for private insurers (Doherty and Dionne 1993; Goodwin and Hungerford, 2014; Mahul, 1999; Miranda and Glauber, 1997). In fact, Li et al. (2020) and Enjolras, Capitanio and Adinolfi (2012) point out that crop insurance often results in failure in commercialization due to the safety premium rate which is required to farmers as a consequence of the level of systemic risk. In the same regard, Skees and Barnett (1999) highlight that the positive correlation across loss events may lead to prohibitive insurance. Duncan and Myers (2000) further emphasize this idea and state that systemic risk is the main factor affecting the failure of the market. In conclusion, the feasibility of a market for crop insurance is highly dependent on how efficiently systemic risk is managed (Shen, 2012).

Authors such as Wang and Zhang (2003) have concluded that correlations between yield losses fade out rather quickly as distances between fields increase. Based on these results, several articles have suggested that geographical diversification may be a good alternative to reduce the degree of systemic risk. As mentioned in the introduction, this study pursues analyzing whether geographical diversification can actually mitigate the systemic risk faced by weather index-based insurance providers and comparing the effect that this can have for temperature- and rainfall-based insurance. This requires the accurate quantification of the degree of dependence between weather states at different locations. Several methodologies have been suggested in the literature for this purpose. The most common approach was followed by authors such as Goodwin (2001), Holly Wang and Zhang (2003) and Woodard and Garcia (2008), who evaluated risk pooling efficiency in US. They used simple correlation coefficients to measure dependence between yields at different stations as a function of distance. However, simple correlations cannot capture the frequent nonlinear dependencies between weather variables. To overcome this limitation, the use of multivariate copula-based models has been recently suggested. This technique was first applied for this purpose by Xu et al. (2010), who focused on the German agricultural industry and addressed both temperature- and rainfall-based policies. However, the statistical reliability of this study was limited, as it was based on a small sample. This limitation was overcome later by Okhrin, Odening, and Xu (2013), who derived a greater sample from a daily model for the temperature variable in China. These authors utilized multivariate asymmetric Archimedean copulas. The same methodology was applied by Awondo (2019) to assess drought risk in Africa. However, this author, who also relied on a daily model to derive a bigger sample, approached rainfall instead of temperature. Also focusing on precipitation, Nguyen-Hui et al. (2019) suggested for the case of Australia the use of vine copulas as a method to overcome some of the disadvantages of the Archimedeans, such as the assumption of the same dependence structure for all pairs or the use of the same copula function (Odening, Musshoff and Xu, 2007; Nguyen-Huy et al. 2017, 2018a, 2019).

3. Data and Methodology

Daily temperature and rainfall data for the periods 1970-2018 and 1964-2018 respectively have been retrieved from the Spanish National Meteorological Agency, AEMET (Agencia Estatal de Meteorología). Although Spain is overall temperate, different regional climates can, indeed, be distinguished. Therefore, we selected 10 weather stations spread throughout whole Spain, aiming at covering the main regional areas of the country: Vigo, Gijon, Zaragoza, Barcelona, Valladolid, Madrid, Valencia, Sevilla, Malaga and Las Palmas de Gran Canaria. Figure 1 displays the location of these cities in the Spanish geography and Table 1 exhibits the distance in km between each pair of locations. The first group of cities is comprised by Vigo and Gijon. Despite their geographical distance and slightly different climatic characteristics, they both belong to the Oceanic or Atlantic climate, which is characterized by frequent and intense precipitations throughout the year. Rainfalls are more recurrent in winter and less common in summer, while temperatures are overall mild and stable. For their part, Sevilla, Madrid, Zaragoza and Valladolid, each with its specificities, belong to the Continental Mediterranean climate, which is marked by cold winters and hot summers. Precipitation is scarce and variable and it is mostly recorded in autumn and spring. Temperatures range considerably. The next group is comprised by Malaga, Barcelona and Valencia. These three cities belong to the Coastal Mediterranean climate, which is characterized by a moderate temperature range, with hot summers and soft winters. Rainfall is scarce and changeable and takes place mainly in autumn and spring. Finally, Las Palmas de Gran Canaria is classified within the Subtropical climate, which is given by warm temperatures throughout the year, with very low volatility and scarce rainfall at the sea level.

Table 1. Distance matrix.

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
2	287.7								
3	650.8	443.2							
4	907.2	685.3	256.6						
5	336.9	222.7	318.7	574.9					
6	465.3	382.3	272.9	505.4	161.9				
7	766	630.4	246.1	303.2	440.2	302.6			
8	587.8	683.6	644.3	829.5	486.2	390.2	540.4		
9	715.9	764.6	626.7	769.8	548.9	415.6	467.6	157.3	
10	1682.8	1923.4	1999.8	2174.3	1790.5	1737.5	1873.5	1355.9	1406.2

Notes: 1: Vigo; 2: Gijon; 3: Zaragoza; 4: Barcelona; 5: Valladolid; 6: Madrid; 7: Valencia; 8: Sevilla; 9: Malaga; 10: Las Palmas de Gran Canaria. Distance is measured in km.

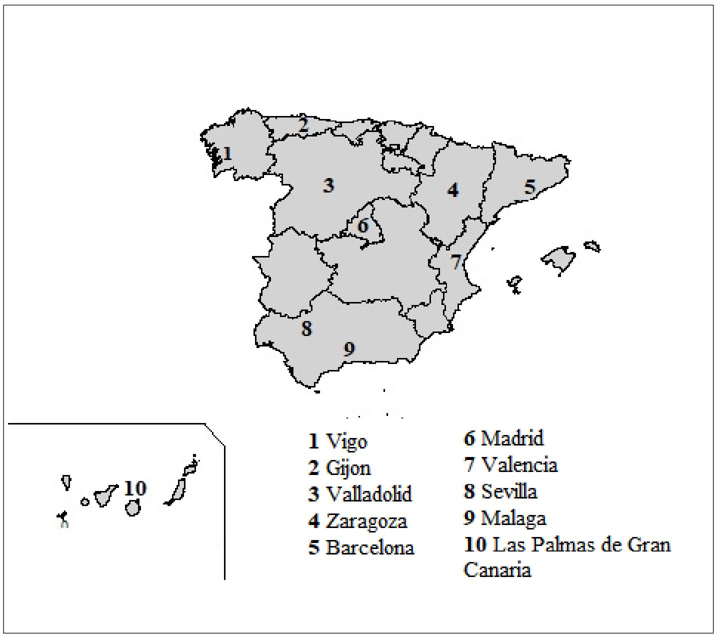

Figure 1. Location of the meteorological Spanish stations.

The next subsections address the different steps followed in this study to assess risk pooling efficiency. First, we choose different meteorological indices that may be suitable underlyings for crop insurance policies. Next, we define the measures employed to evaluate risk pooling effectiveness as a function of the trading area. At this stage, we also show how the cities are clustered for the measurement of the diversification effect. Finally, in pursuance of increasing accuracy, we simulate daily temperature and rainfall data, which are then used to build the weather indices previously selected and to calculate the measures proposed to assess the degree of systemic risk.

3.1.Selection of weather indices

Any weather index-based insurance policy requires the selection of an underlying that describes the evolution of the meteorological variable of interest with accuracy. In this study, we choose the indices HDD (Heating Degree Days), CDD (Cooling Degree Days) and CR (Cumulative Rainfall) as underlyings, which have been widely proposed and applied in the agricultural-related literature.

The HDD index is defined as:

$$HDD_{y,z} = \sum_{i=1}^{I} \max\ (0, 18ºC - T_{i,y,z}),$$

(1)

where $T_{i,y,z}$ denotes the average temperature registered on day i and year y at station z, measured in Celsius degrees. This index is calculated for the winter period, comprised between November 1st and March 31st.[1]

For its part, the CDD index is defined in the following form:

$$CDD_{y,z} = \sum_{i=1}^{I} \max\left(0, T_{i,y,z} - 18ºC\right)$$

(2)

Its period of calculation is comprised between May 1st and September 30th.

Finally, the CR index is defined as:

$$CR_{y,z} = \sum_{i=1}^{I} R_{i,y,z},$$

(3)

where R_i denotes the rainfall registered on day i and year y at station z, measured in millimeters. As for the CDD measure, this index is calculated for the period comprised between May 1st and September 30th.

The descriptive statistics of the three indices considered, based on real data, are exhibited in Table A1 of the Appendix.

The indices' calculation allows for the derivation of insurance payoffs. Indemnities for the temperature-based policies are generated whenever the temperature index exceeds a given level, called strike.[2] These indemnities are calculated as the difference between the index value and the strike, which is then multiplied by the tick size (for the purpose of deriving a monetary value). In this study, this parameter is fixed at a value of 1 monetary unit. Regarding rainfall, the insurance scheme proposed provides coverage against drought. Indemnities are, therefore, generated whenever the strike level[3] exceeds the CR

[1] The index is computed for the same period as for the contracts supplied by Chicago Mercantile Exchange (CME).

[2] We suggest three different strike values, equal to the 0.55, 0.70 and 0.85 empirical quantiles of the historical HDD and CDD.

[3] Strikes are defined in this case as the 0.15, 0.30 and 0.45 empirical quantiles of the historical CR.

index. They are computed as the difference between both values, which is then multiplied by the tick size.

3.2. Assessment of the diversification effect

As explained in section 3.1, indemnities can be derived from the weather indices selected. Those indemnities allow us to calculate the losses experienced by insurers, from which risk pooling effectiveness can be assessed. However, we first need to define a measure to perform this analysis.

The previous literature aiming to ascertain whether risk pooling effectiveness varies as a function of the trading area has evaluated the degree of systemic risk via the Value at Risk (VaR) of the net losses faced by the insurance company (Holly Wang and Zhang, 2003; Okhrin, Odening, and Xu, 2013; Awondo, 2019). This can be expressed as follows:

$$VaR_{\alpha}(X) = inf\{X|P\ (X \geq x) = 1 - \alpha\}, \tag{4}$$

where $inf\{X|A\}$ is the lower limit of *X* given event A; and $1 - \alpha$ denotes the ruin probability (Okhrin, Odening, and Xu, 2013). Dividing VaR by the number of contracts gives the Buffer Load (BL), which is the risk loading that has to be added to the fair price of the insurance to avoid bankruptcy.

In this case, *X* (losses) is defined as:

$$X = \sum_{z=1}^{n} w_z \left(F_{I_{y,z}} - \pi_z\right), \tag{5}$$

where $F_{I_{y,z}}$ is the indemnity payment as a function of the weather index *I*, whose calculation was explained in section 3.1. Therefore, *I* can take the form of HDD, CDD, and CR*;* π_z denotes the fair insurance premium for region *z*, computed as the expected value of the indemnity ($E[F_{I_{y,z}}]$); and w_z is the weight of the *z*th insurance contract in the company portfolio (Okhrin, Odening, and Xu, 2013).

Although Value at Risk (VaR) has become a standard risk measure, it is associated to some deficiencies (Artzner et al., 1997, 1999; Rootzén and Klüuppelberg, 1999; Acerbi, Nordio, and Sirtori, 2001). In fact, it has been heavily criticized for not being sub-additive, meaning that a portfolio risk can exceed the sum of the degree of risk of its individual components. Furthermore, it does not consider the severity of an incurred damage event (Acerbi and Tasche, 2002). In other words, it does not take into account any loss beyond the VaR level. This is referred to in the literature as the “tail risk”. As a consequence, other so-called coherent risk measures have been suggested. One of the most well-known is the Expected Shortfall (ES), which is defined as “the conditional expectation of losses beyond the VaR level” (Yamai and Yoshiba, 2005). This measure is expressed as follows (Yamai and Yoshiba, 2005):

$$ES_\alpha(X) = E[X|X \geq VaR_\alpha(X)] \tag{6}$$

At the light of the pitfalls of the VaR measure, we use in this study the ES. For its calculation, we assume uniform weights across regions and set α at a value of 0.95. Therefore, the BL is directly derived from this measure.

Consequently, the diversification effect is calculated in the next form, following Okhrin, Odening, and Xu (2013):

$$DE = \frac{BL_{\alpha_n}^*}{(\sum_{z=1}^n BL_{\alpha_z})n^{-1}}, \tag{7}$$

where DE denotes the diversification effect over the entire geographical area considered, $BL_{\alpha_n}^*$ is the Buffer Load of the whole region, and BL_{α_z} is the individual Buffer Load of location z.

DE is calculated for different levels of aggregation. Concretely, locations are clustered according to the distance between them, using a hierarchical cluster analysis and the Ward2 algorithm (Murtagh and Legendre, 2014). The distance matrix is presented in Table 1.

The resulting dendogram is depicted in Figure 2.

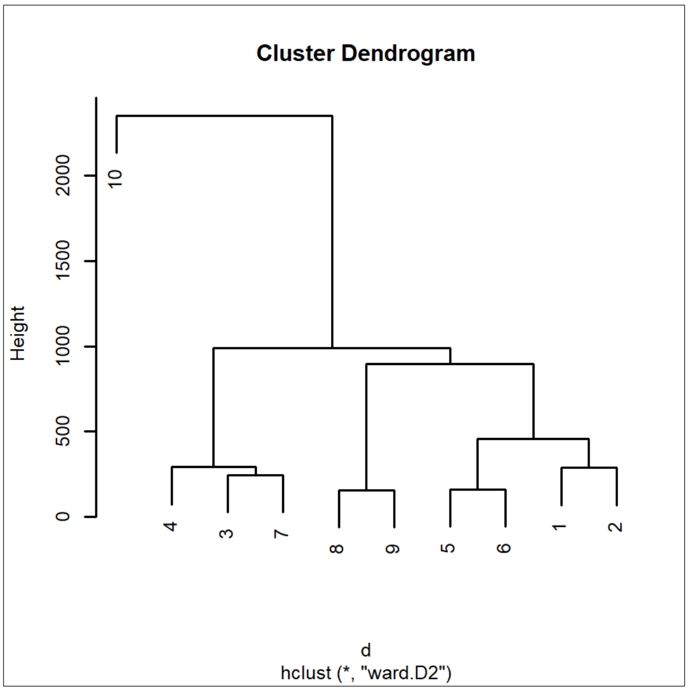

Figure 2. Dendogram (cluster analysis).

Therefore, we suggest the aggregation scheme for the insurance regions exhibited in Table 2.

Table 2. Aggregation of insurance regions.

Aggregation level	**0**	**1**	**2**	**3**	**4**	**5**
Insured area	5	5,6	5,6,1,2	5,6,1,2,8,9	1-9	1-10

Notes: Numbers of the insured area: 1: Vigo; 2: Gijon; 3: Zaragoza; 4: Barcelona; 5: Valladolid; 6: Madrid; 7: Valencia; 8: Sevilla; 9: Malaga; 10: Las Palmas de Gran Canaria.

As mentioned in the introduction, our analysis does not rely on real but on simulated weather data. This is expected to increase the accuracy of the results, given the limited amount of observations that meteorological data allow for. Therefore, the diversification effect that we present is calculated for the simulated samples. The next section reviews the methodology followed to generate weather daily random paths, from which indices and indemnities are derived, as explained in section 3.1.

3.3.Weather variables modelling

Daily temperature and rainfall variables cannot be modelled following the same methodology, as they both have their own specificities. Regarding temperature, it is widely accepted that it can be shaped accurately applying a daily model that relies on the stochastic process called Orstein-Uhlenbeck. However, modelling precipitation is harder than temperature. First, it evolves more irregularly: it is more erratic (Stowasser, 2012). Furthermore, it is not a continuous variable, but a binary event which can take the value of zero or any other positive amount (Alexandridis and Zapranis, 2013). Thus, its distribution is bounded on the left by zero (Shah, 2017). This last fact makes impossible the application of the Orstein-Uhlenbeck process, which can only be used for Gaussian and Markovian processes. The methodology followed to model each of the variables is described in the next subsections.

3.3.1. Multisite temperature modelling

The generation of daily data at the weather stations under consideration requires the development of a multisite temperature model that preserves correlation between weather conditions at different locations. The generating process can be divided into a deterministic and a non-deterministic part.

- <u>Deterministic part</u>

The deterministic part relies on the model proposed by Alaton, Djehiche, and Stillberger (2002), which is based on the Orstein-Uhlenbeck process introduced in the previous section.

The first step consists in capturing the characteristic patterns of the mean temperature: seasonality and time trend. The resulting function is fitted to the daily mean temperatures registered at each of the weather stations considered using OLS. Figure A1 of the Appendix illustrates the good fit attained between real and mean temperatures for a given city.

The next step entails adding noise, which is modelled with a standard Wiener process, to the deterministic mean temperature. Unlike Alaton, Djehiche, and Stillberger (2002), who assumed monthly varying volatility, we suggest varying daily values, following subsequent studies such as Zapranis and Alexandridis (2006) and Benth and Saltyte-Benth (2007), as this decision has proven to be superior in terms of accuracy.

The last stage involves adding a mean reverting process to prevent daily temperatures to deviate from the mean for long-time periods.

Table 3 exhibits the three steps of the deterministic part of the model and the formulas used at each stage. More detailed information on how these expressions were derived can be found in Alaton, Djehiche, and Stillberger (2002).

Table 3. Steps and formulas of the temperature modelling process.

Capturing the seasonality and time trend of temperature by Truncated Fourier series	Modelling the driving noise process: estimating sigma	Estimating the mean reversion parameter
$\boldsymbol{T_t^m} = \boldsymbol{a_1 + a_2 t + a_3 \sin(\omega t) + a_4 \cos(\omega t)}$,	$\sigma_t W_t$, $t \geq 0$	$\hat{a}_n = -\log\left(\frac{\sum_{t=1}^{n} Y_{t-1}\{T_t - T_t^m\}}{\sum_{t=1}^{n} Y_{t-1}\{T_{t-1} - T_{t-1}^m\}}\right)$,
Where $\boldsymbol{T_t^m}$ is the mean temperature, t=1, 2, …, denotes January 1, January 2 and so on; and ω is the period of the oscillations, which is equal to $\frac{\boldsymbol{2\pi}}{\boldsymbol{365}}$, or equivalently, to one year.	Where $\sigma_{t+365} = \sigma_t$ and W_t is a standard Wiener process.	Where $\hat{a}_n$ is the mean reversion parameter and $Y_{t-1} \equiv \frac{T_{t-1}^m - T_{t-1}}{\sigma_{t-1}^2}$ $t = 1,2,\ldots,n$

- <u>Non-deterministic part</u>

Once the stochastic process is completely defined, the non-deterministic part of the model comes into play. According to Kordi (2012, pp.46-47), random temperature paths can be generated with the following equation:

$$T_j = (1 - a)(T_{t-1} - T_{t-1}^m) + T_t^m + \in_t \sigma_t, \tag{8}$$

where $\in_{t=1}^{N-1}$ are independent standard normally distributed random variables.

Usually, temperature random paths are directly obtained from equation (1), by making $\in_{t=1}^{N-1}$ vary randomly. However, as we are dealing with the generation of data at multiple sites, correlation levels between standard errors should be preserved. To ensure this, we follow the approach suggested by Wilks (1998) and latter refined by Mhanna and Bauwens (2011). Although these articles deal with the simulation of rainfall at multiple sites, their generating process can be perfectly extrapolated to the generation of temperature standard residuals. Figure 3 shows the steps of this procedure.

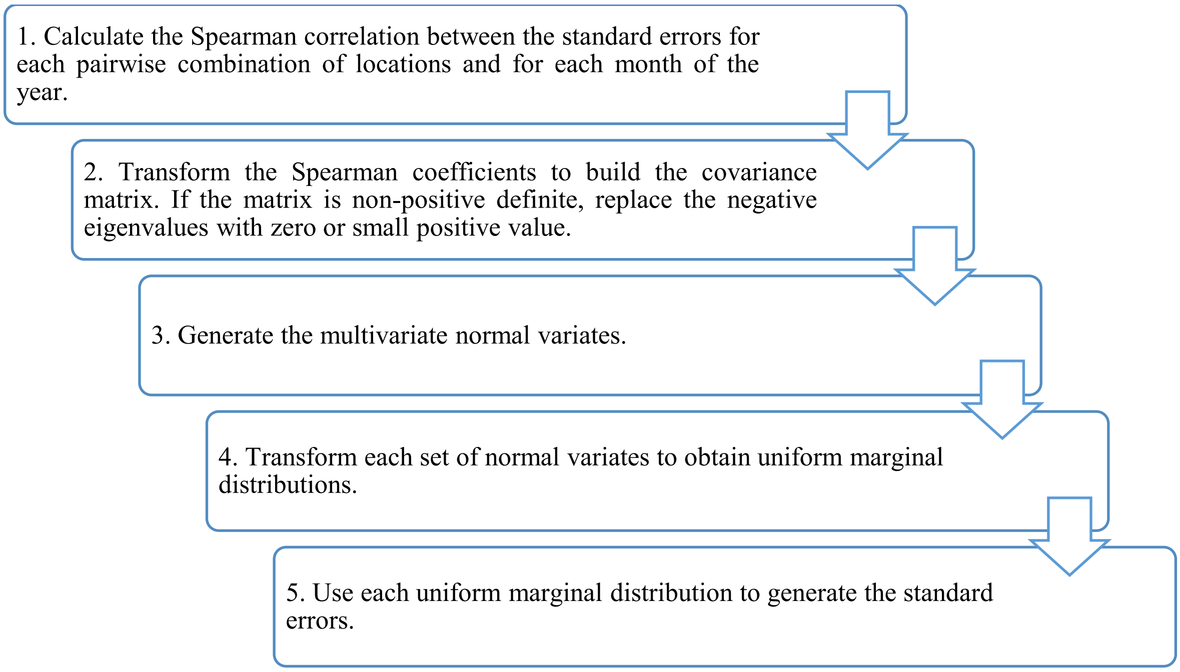

Figure 3. Steps of the multisite standard errors generating process. (color online only)

As stated by Mhanna and Bauwens (2011), the first step of the multisite standard errors generating process involves determining the Spearman rank correlation coefficient for each pairwise combination of standard errors and for each month of the year, as shown in Figure 3. Binormal correlations are then derived as stated in equation 9. This corresponds to the second step exhibited in Figure 3.

$$\varphi(k,l) = 2\sin\left[\pi\frac{\rho(k,l)}{6}\right], \tag{9}$$

where $\rho(k,l)$ denotes the Spearman correlation between locations k and l.

The second stage continues with the construction of the covariance matrix, whose elements are the binormal correlations. If it is non-positive definite, we replace the negative eigenvalues with a zero or a small positive value.

The third stage entails generating the multivariate normal variates as follows:

$$w_t = UR_t, \tag{10}$$

where R_t denotes an independent normal vector, generated randomly from a standard normal distribution, and U is a coefficient matrix such that:

$$U^T U = \Omega, \tag{11}$$

where Ω represents the covariance matrix built in the previous step.

The fourth stage consists in transforming each set of normal variates to obtain uniform marginal distributions. We use the R command pnorm() for this purpose. Finally, we generate the standard errors from each uniform marginal distribution using the command qnorm() with mean 0 and standard deviation 1.

Once this process has been concluded, daily temperature is simulated for all the cities considered by adding both the deterministic and non-deterministic part of the model. Next, the HDD and CDD indices are built and their indemnities computed as explained in Section 3.1.

3.3.2. Multisite rainfall modelling

As for temperature, we need to develop a model that allows the multiple simulation of daily rainfall data at several weather stations. We follow the approach presented by Wilks (1998) and later refined by Mhanna and Bauwens (2011). As suggested by these authors, we divide the rainfall process into two sub-processes: occurrence and amount.

- <u>Occurrence process</u>

We start by explaining the occurrence process. First, we need to calculate for each month and location the parameters P_{01}, which denotes the conditional probability of a wet day if the previous day was dry, and P_{11}, which is the conditional probability of a wet day given that the previous day was wet. These can be calculated as:

$$\hat{P}_{01}(k) = \frac{n_{01}(k)}{n_{01}(k) + n_{00}(k)},$$

(12)

$$\hat{P}_{11}(k) = \frac{n_{11}(k)}{n_{11}(k) + n_{10}(k)},$$

(13)

where, for the weather station *k*, n_{01} is the historical number of dry days followed by wet days, n_{00} denotes the historical count of dry days followed by dry days, and so on.

The second step of the occurrence process consists in constructing the covariance matrix analytically. For this purpose, we calculate the gamma coefficient for each pair of locations *k* and *l* as follows:

$$\gamma(k,l) = \frac{\varphi(k,l) - 1}{\varphi(k,l) + 1},$$

(14)

where φ is the odds-ratio and is computed in the following form:

$$\varphi(k,l) = \frac{\pi_{00}(k,l)\pi_{11}(k,l)}{\pi_{10}(k,l)\pi_{01}(k,l)},$$

(15)

where π_{00} denotes the joint probability that station pairs are both dry, π_{11} denotes the joint probability that station pairs are both wet, and so on. For instance, π_{00} is derived as:

$$\pi_{00}(k,l) = \frac{d_{joint}}{n},$$

(16)

where d_{joint} is the historical number of station pairs that are dry on the same day and *n* denotes the total number of data values.

In this case, the elements of the correlation matrix Ω are the gamma coefficients instead of the binormal correlations.

The next steps coincide with those applied in the multisite standard errors generating process exhibited in Figure 3 (steps 3 to 4). For this purpose, we need to apply equations 10 and 11.

- <u>Amount process</u>

This section approaches the amount process. The first stage involves modelling rainfall amounts on wet days[4] for each month and location with a 2-parameter Gamma distribution, which is defined by the shape (α) and scale (β) parameters. Both are estimated by MLE (Maximum Likelihood Estimation). Please, refer to Mhanna and Bauwens (2011) for a more detailed explanation of this distribution.

The second step entails computing Spearman correlations between the amounts of rain recorded in wet days for each month and pair of locations.

The subsequent steps coincide with those shown in the multisite standard errors generating process depicted in Figure 3 (steps 2 to 4); this is, we need to apply equations 9, 10 and 11.

Once both the occurrence and amount processes have been defined and the uniform marginal distributions have been generated, we proceed to simulate rainfall amounts.

For the generation of occurrences, each uniform marginal distribution is used individually. First, we need to decide which conditional probability to utilize as follows:

$$P_c(k) = \begin{cases} P_{01}(k) & if \quad x_{t-1}(k) = 0 \\ P_{11}(k) & if \quad x_{t-1}(k) = 1 \end{cases} \tag{17}$$

Next, we can directly simulate occurrences as:

$$X_t(k) = \begin{cases} 1 & if\ \Phi(v_t(k)) \leq P_c(k) \\ 0 & otherwise \end{cases}, \tag{18}$$

[4] In this study, "wet" means occurrence of at least a minimum precipitation amount for the day of 0.1 mm.

where $\Phi[.]$ denotes the standard cumulative distribution function (CDF); and v_t denotes the standard Gaussian variates of the occurrence process.

Regarding the amounts, they are directly simulated as the inverse of the Gamma distribution, with the parameters estimated in the first step, applied to the uniform marginal distributions generated in the last step of the amount process. Concretely, the R command qgamma() is used for this objective.

Finally, rainfall data are generated by multiplying the occurrence, which can take the value of 0 or 1, by the amount.

Once daily rainfall data have been generated, the cumulative rainfall index can be computed for each of the cities under consideration and their generated indemnities can be calculated as explained in Section 3.1.

4. Results and discussion

As introduced in Section 1, one of the main goals pursued in this study is comparing the degree of systemic risk implied by temperature- and rainfall- based insurance. We expect precipitation contracts to yield lower systemic risk levels than those geared to temperature, given the more erratic and less geographically correlated behavior of this meteorological variable. The next subsections show and discuss the results attained in this regard.

4.1. Assessing the losses' descriptive statistics

As an initial explorative analysis to approach this issue, Table 4 exhibits the descriptive statistics of the losses X faced by the insurer as defined in equation 5, with n=10. This shows the degree of risk implied by each of the suggested contracts and their earnings potential.

Table 4. Descriptive statistics of losses.

Losses	Min	Q1	Median	Q3	Max	SD
			Strike 1			
CR	-3.02	-3.02	-1.61	1.58	33.55	4.17

CDD	-4.721	-4.72	-2.63	1.77	55.53	7.12
HDD	-6.65	-6.65	-4.96	2.52	86.64	11.02
			Strike 2			
CR	-7.81	-5.75	-1.94	3.61	49.95	7.40
CDD	-12.03	-9.05	-3.64	4.42	78.33	12.44
HDD	-16.09	-14.11	-7.05	6.83	118.65	19.33
			Strike 3			
CR	-15.09	-8.30	-1.98	6.37	62.06	10.86
CDD	-21.21	-12.62	-4.30	8.12	92.13	17.00
HDD	-29.10	-21.35	-8.18	13.78	139.39	27.53

Notes: Strike 1, 2 and 3 correspond to the 0.85, 0.70 and 0.55 empirical quantiles respectively for the temperature-based indices and to the 0.15, 0.30 and 0.45 concerning the rainfall-based index.

Based on the results displayed in Table 4, we observe that CR insurance actually entails lower risks from the insurer’s perspective as compared to CDD and HDD contracts. In fact, these last type of policies yield lower figures for the maximum value, third quartile and standard deviation. These descriptive statistics are further commented subsequently. Regarding the first of them, and for the strike level 1, the maximum loss implied by rainfall-based contracts is 33.55€, which is significantly lower than that attained for CDD (55.53€) and HDD policies (86.64€). The same pattern is found for the remaining strike levels considered.

A similar behavior is found for the third quartile. For this descriptive statistic and the first strike level, CR-based contracts yield lower losses (1.58€) as compared to CDD (1.77€) and HDD (2.52€) insurance. The same happens for the second and third strike level. All these findings show that temperature-based contracts are more prone to generate greater losses than those geared to rainfall. However, this will be further discussed below based on the Buffer Load figures exhibited in Table 5.

The third descriptive statistic of those mentioned above is the standard deviation, which is a measure of the risk faced by insurers. Again, lower values are attained for CR-based contracts as compared to those geared to temperature. For the strike level 1, the standard deviation of this insurance modality amounts to 4.17€, which is followed by CDD (7.12€) and HDD (11.02€) policies respectively. Again, the same pattern is identified for the remaining strike values.

As expected, and at the light of the results attained, CDD- and, especially, HDD-based policies show greater losses but also greater earnings potential than those geared to rainfall. As displayed in Table 4, these contracts yield higher absolute figures for the minimum value, first quartile and the median. This is not surprising based on the previous findings, as these contracts are also riskier. For instance, for the strike level 1, the absolute minimum losses (maximum gains) are 3.02€, 4.72€ and 6.65€ for CR, CDD and HDD contracts respectively. As observed, the maximum gains entailed by HDD contracts are more than twice the value attained for rainfall policies. The same behavior is observed for the remaining strike levels.

Regarding the first quartile, similar conclusions are reached. Again, HDD contracts yield the most favorable results. For the first strike, the absolute value of this statistic amounts to 3.02€, 4.72€ and 6.65€ for CR, CDD and HDD policies respectively. The same pattern is identified for the second and third strike level. In fact, for all the strikes considered, the value of this statistic for HDD policies more than doubles the figures derived for rainfall contracts.

Similar results are attained for the third descriptive statistic: the median. It should be noted that, for all the strike values considered, the value of this statistic is significantly greater for HDD insurance as compared to CR contracts, being in all cases more than three times higher. For instance, for the first strike, HDD-based insurance yields again the highest absolute value (4.96€), followed by CDD-based contracts (2.63€) and CR policies (1.61€). Similar results are reached for the remaining strike levels.

At the light of these results, it seems clear that insurance firms would need to balance carefully the type of contracts supplied. Temperature-based insurance, which is the most commonly traded insurance typology, yields higher earnings potential but results riskier than rainfall insurance. For its part, rainfall policies show lower earnings potential in exchange for lower income variability. Therefore, insurance companies may actually consider offering contracts geared not only to temperature but also to rainfall for the purpose of reducing their risk exposure.

4.2. A step further: assessing the degree of systemic risk through the Buffer Load (BL)

Table 5 sheds more light on the quantification of the degree of systemic risk implied by temperature- and rainfall-based insurance. This table exhibits the BL figures attained as a function of the degree of geographical aggregation. The higher the BL measure, the more expensive weather insurance would be for farmers. In line with the conclusions derived from Table 4, it is observable that rainfall-based policies imply lower systemic risk in comparison to the most commonly supplied temperature-based insurance, given the lower BL figures attained for this type of contracts for all the strikes and aggregation levels contemplated.

The values displayed in Table 5 also contribute to the assessment of the other goal of this study, which is discerning whether an increase in the trading area can reduce systemic risk. Although this is analyzed more accurately in Table 6, it is observable that BL generally decreases the higher the level of aggregation, as defined in Table 2. For the first strike level, the BL value ranges for CR-based contracts between 35.81€ and 13.02€ for the lowest and the highest degree of aggregation respectively. This range is greater for CDD-based insurance (comprised between 68.25€ and 23.85€) and even higher for HDD-based contracts (comprised between 110.66€ and 36.20€). The same pattern is observed for the second and third strike levels. It should be noted that, in all cases, the figures attained for the lowest aggregation level are more than double the figures of the highest aggregation level. These findings support the hypothesis that broadening the trading area may have favorable effects and increase the feasibility of a market for weather index-based insurance in Spain.

Table 5. Expected shortfall as a function of the degree of aggregation.

			CR			
Aggregation level	0	1	2	3	4	5
BL (strike 1)	35.81	22.91	25.66	17.90	14.46	13.02
BL (strike 2)	52.48	35.89	38.29	27.76	22.69	20.43
BL (strike 3)	62.72	45.06	49.95	37.05	30.38	27.36
			CDD			
Aggregation level	0	1	2	3	4	5
BL (strike 1)	68.25	63.30	36.75	30.29	26.25	23.85

BL (strike 2)	96.25	96.24	56.81	46.89	41.34	37.80
BL (strike 3)	110.96	115.85	70.46	58.09	51.69	47.33
			HDD			
Aggregation level	0	1	2	3	4	5
BL (strike 1)	110.66	85.74	59.43	45.26	40.12	36.20
BL (strike 2)	152.55	128.89	91.71	70.94	64.03	57.57
BL (strike 3)	181.99	158.98	116.39	91.07	83.41	75.24

Notes: Strike 1, 2 and 3 correspond to the 0.85, 0.70 and 0.55 empirical quantiles respectively for the temperature-based indices and to the 0.15, 0.30 and 0.45 concerning the rainfall-based index.

4.3. Concluding on the relationship between geographical diversification and systemic risk

Table 6 directly addresses the assessment of the effect of geographical diversification on the level of systemic risk. This table exhibits the results attained for each of the suggested insurance schemes for the highest level of aggregation in terms of fair price and diversification effect. Concerning fair prices, we observe that CR-based policies are the cheapest, followed by CDD- and HDD-geared contracts. For the first strike level, the fair price of the HDD policies (6.65€) is more than 1.4 times higher than the price of CDD insurance (4.72€) and more than doubles the value attained for CR-based contracts (3.02€). The same pattern is observed for the remaining strike levels.

Regarding the diversification effect, results are also more favorable for rainfall-based contracts. This is measured as the ratio of the BL of the whole region to the average individual BL of each location, as introduced in equation 7. Therefore, the lower this measure, the higher the systemic risk reduction. For the strike value 1, the diversification effect of the CR contracts is 0.35, followed by CDD (0.40) and HDD (0.45) insurance. For the second strike, the diversification effect grows for all types of contracts, with a value of 0.39 for the CR insurance and 0.45 and 0.50 for CDD- and HDD-based policies, respectively. The diversification effect is at its highest for the third strike, with figures of 0.42, 0.47 and 0.55 for CR-, CDD- and HDD-based contracts, respectively. It is worth noting that diversification reduces the degree of systemic risk more pronouncedly when only the negative extreme events are insured (this is, for the strike value 1). This result is coherent, as extreme meteorological conditions usually show higher correlation than normal weather states (Goodwin, 2001).

Table 6. Fair prices and Diversification Effects (whole insurance area).

	Cumulative rainfall		
	Strike 1	**Strike 2**	**Strike 3**
Fair price	3.02	7.81	15.09
Diversification effect	0.35	0.39	0.42
	CDD		
Fair price	4.72	12.03	21.21
Diversification effect	0.40	0.45	0.47
	HDD		
Fair price	6.65	16.08	29.07
Diversification effect	0.45	0.50	0.55

Notes: Strike 1, 2 and 3 correspond to the 0.85, 0.70 and 0.55 empirical quantiles respectively for the temperature-based indices and to the 0.15, 0.30 and 0.45 concerning the rainfall-based index.

5. Conclusion

This study assesses the degree of systemic risk implied by a market for weather index-based insurance in Spain. This country is suitable for the analysis, given the high weight of the agricultural industry in its productive structure and the fact that it is expected to be highly affected by climate change. In 2018, the premiums collected by the Spanish System of Combined Agricultural Insurance, which offers loss-based contracts, amounted to 738.52 million euros and 419565 policies were agreed (Agroseguro, 2020). This shows the importance of supplying a feasible hedging alternative in this country. Given that weather-index based insurance overcomes several of the drawbacks of the loss-based typology, this modality would likely experience a high demand if it were offered at a national level.

Given the potential demand that weather index insurance could have in Spain, we evaluate whether broadening the trading area for this modality would reduce correlation in losses and, thus, the probability of bankruptcy for insurance firms. Furthermore, we compare the degree of systemic risk implied by temperature- and rainfall-based contracts. For this purpose, we suggest insurance schemes based on weather indices. To ensure accurate results and conclusions, we use meteorological daily models, from which we derive greater data samples. The results attained point out that the higher the aggregation level (the broader the trading area), the lower the Buffer Load (as measured by Expected Shortfall) that has to be charged to farmers. Our results also suggest that, although temperature-based contracts show higher earnings potential, rainfall-based policies imply lower maximum losses and risks and, at the same time, result cheaper and show lower values for the diversification effect (the lower this figure, the lower the correlation in losses and the degree of systemic risk). Finally, our findings highlight that aggregation results especially beneficial for the strike value 1 (0.85 empirical quantile for temperature-based contracts and 0.15 for rainfall-geared policies), as extreme weather events are more correlated than normal conditions (Goodwin, 2001).

In sum, the main conclusion of this article is that the supply of weather index-based insurance should not be focused on a specific region or county. Instead, it should consider the different regional climates in Spain to ensure that correlation in losses is moderate and, thus, that the level of systemic risk is acceptable. It is well known that basis risk increases as the distance between the place for which insurance is purchased and the meteorological station where measurements take place increases. However, we believe that not necessarily an increase in the trading area may always lead to higher levels of basis risk if there is an enough spread network of weather stations. This issue has also been addressed recently by several authors, such as Kölle et al. (2020) and Vroege et al. (2021) among others, who suggest as a suitable solution the use of satellite images. Furthermore, in this study we state that the inclusion of rainfall-based policies would be highly beneficial, given the lower levels of correlation in terms of precipitation among locations and the stronger diversification effect attained for this weather variable. Therefore, insurance firms should contemplate the supply of these contracts, jointly with temperature-based policies, in order to reduce their systemic risk exposure. For their part, public endeavors, which have so far been focused on the loss-based typology offered by the Spanish System of Combined Agricultural Insurance, should also concentrate on weather-index insurance, for instance, by contributing to the development of a market for this type of contracts (as done previously for the loss-based modality, which ended up with the creation of the Spanish System of Combined Agricultural Insurance) or by increasing farmers' awareness of the existence of these type of policies once they started being traded. Government efforts might also be focused on the development of a spread enough network of weather stations, on ensuring the accuracy of their weather measurements, and even on the development of more advanced measurement techniques (based, for instance, on satellite images).

It is worth noting that this study compares the degree of systemic risk implied by a market for rainfall- and temperature-based policies. However, it does not consider the connection between both weather variables. Supplying both types of contracts at the same time may, indeed, reduce the degree of risk faced by insurers significantly, given the lower dependence between these two variables at a national level (e.g. the rainfall recorded in Sevilla is weakly correlated to the temperature registered in Vigo). Future research lines could, therefore, focus on this issue and develop a model that allows the simultaneous generation of both temperature and precipitation, as this would help to quantify the overall risk faced by insurance entities. As a final remark, we would like to point out that the feasibility of a market for weather index-based insurance in Spain would finally rely upon the farmers' degree of risk aversion and, thus, upon their willingness to pay. Would they be willing to pay the buffer loads (as measured by Expected shortfall) displayed in Table 5? This question may also be addressed in future research, for instance, through surveys.

Last but not least, as stated throughout the paper, although this study addresses a specific country, Spain, the methodology applied is suitable to be extrapolated straightforward to other geographical areas.

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Appendix

Table A1. Descriptive statistics of the weather indices.

	1	2	3	4	5	6	7	8	9	10
					Cumulative rainfall					
Mean	383.72	279.46	129.19	234.80	144.84	115.81	141.40	77.83	57.44	9.34
Median	387.30	252.50	125.90	221.10	139.50	107.00	117.80	76.40	50.10	5.10
SD	125.55	89.33	56.92	104.53	57.11	48.11	77.40	44.75	40.18	14.63
					HDD					
Mean	1365.51	1253.75	1600.03	1306.61	2037.24	1700.07	884.69	953.97	835.36	108.50
Median	1363.31	1251.91	1625.24	1301.70	2055.93	1702.13	900.82	946.56	825.14	102.90
SD	105.75	109.79	122.29	125.65	123.91	117.76	108.59	116.49	87.92	54.65
					CDD					
Mean	141.76	90.24	546.36	412.78	187.16	557.67	666.92	920.17	678.99	624.20

Median	131.67	83.35	553.45	416.57	179.72	567.42	675.43	936.70	683.10	622.05
SD	53.68	40.73	86.82	94.47	52.03	87.74	76.54	100.57	63.09	75.10

Notes: 1: Vigo; 2: Gijon; 3: Zaragoza; 4: Barcelona; 5: Valladolid; 6: Madrid; 7: Valencia; 8: Sevilla; 9: Malaga; 10: Las Palmas de Gran Canaria.

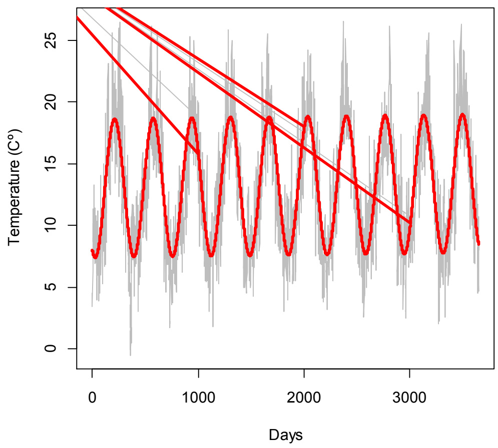

Figure A1. Mean and real temperatures at Vigo station over 10 years. (color online only)