

CHAPTER 2: REVIEW OF LITERATURE

The literature was reviewed on the following two aspects: (a) basis risk, and weather data analysis & climate trends. These are outlined in this chapter.

2.1. MEASUREMENT OF WEATHER RISK

Weather events that impact crop yields are often spatially correlated, thus creating problems for traditional insurance, which is designed to pool a large number of small, uncorrelated risks rather than widespread systemic losses (Miranda and Glauber, 1997).

Vedenov and Barnett (2004) have analyzed the risk-reducing performance of weather derivatives by comparing producers' revenues with and without the insurance contract. Three different criteria were used by them to *measure* the change in risk exposure experienced by producers who bought the designed contracts - the mean root square loss (MRSL), value-at-risk (VaR), and certainty-equivalent revenues (CERs).

Miranda and Glauber (1997) have argued that the existence of systemic weather risk constitutes the main cause for the failure of private crop insurance markets unless efficient and affordable instruments for transferring this risk are available. This conjectures based on the observation that the existing crop insurance programs, including drought risk, are either subsidized (e.g. United States of America or Canada) or have negligible participation rates (as in Germany). However, there are several possible instruments that allow handling of systemic risks, among them are reinsurance or weather derivatives (Xu, Odening and Musshoff, 2008, quoted in Guenther Filler *et al.*, 2009). Alternatively, an insurance provider may try to spatially diversify systemic weather risk by increasing its trading area. In order to identify the appropriate measures for coping with systemic weather risk, it is necessary to quantify these risks (Guenther Filler *et al.*, 2009).

Alan Fuchs and Hendrik Wolff (2011) have found that not only the minimum amount of cumulative rainfall in each period is important, but it is the variance within that period also. Therefore, they have suggested an additional index, which counts the number of days with a positively measured rainfall minimum. If the minimum number of rainfall days is not reached, then the indemnity payment is triggered.

The use of degree-days as a measure of risk represents a broad seasonal measure of risk. It is only specific to the time frame in question (e.g., June 1-August 31) and represents more or less the intensity of broad temperature risks. An alternative approach is to examine specific events. However, previous studies on weather derivatives have focused on a single risk event, even though stress events that happen in combination often have negative effects more onerous than stress events happening independently. Some stress events may be considered jointly for accurate compensation of losses, such as heat stress and drought, which have a strong negative effect in correlation (Mittler, 2006, quoted in Michael Norton, 2009). One application of this “joint-risk” analysis is the pricing of insurance premiums for specific crop disease risks which flourish in the observed combinations of temperature and/or rainfall. It may be possible to insure for joint risk events directly by insuring the underlying weather events that bring about the determinable loss (Norton, 2009).

In view of the relevance of spatial dependence of weather events for crop insurance, it is not surprising that some attempts for quantification have already been 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) have applied the same technique to US yield data (Wei Xu *et al.*, 2010).

Guenther Filler *et al.* (2009) have modeled and estimated the losses of a weather-related insurance at different regional levels and different aggregation levels. They assumed that the indemnity payments, directly or indirectly, depend on the weather indices measured at several locations. They have concentrated on the tail behavior of the joint loss distribution as the probability of big losses is crucial for the required buffer fund of the insurer and the premium loading above the expected payoff and thus for the viability of an index-based crop insurance. For that purpose the probability distribution of the joint losses was estimated using copulas. Once the copula function and marginal distributions of the weather indices have been determined the value-at-risk (VaR) of the insurers total losses can be calculated by means of stochastic simulation. By comparing results of different copula types with those from simple correlations they have contributed to the discussions on appropriate modeling of statistical dependencies in the context of weather insurance.

Wei Xu *et al.* (2010) have used copulas as an alternative to linear correlations since they have allowed greater flexibility in modeling the dependence structure of insurance losses in different regions. Copulas have also been used in the field of climate and meteorological research (e.g., Schoelzel and Friederichs, 2008). Applications in an agricultural context, however, are rare. Vedenov (2008) has analyzed the relationship between individual farm yields and area yields and Zhu, Ghosh and Goodwin (2008) have investigated the dependence of prices and yields in the context of revenue insurance (quoted in Wei Xu *et al.*, 2010).

Antoine Leblois *et al.*, (2011) have found that the actual sowing date to determine the beginning of the crop growth period in an insurance contract is difficult to identify because it cannot be observed costless by the insurer. Thus, they compared two growth phase schedules [First, the observed and second, the simulated following Sivakumar, (1988) rainy season criteria, defining the beginning and the end of the growing season]. A further complexity is indistinguishing various phases during the crop growth period in the calculation of the index. Hence, they have used the weighted average of millet critical growth phases cumulative rainfall following and crop model (SARRA-H), calibrated on this area for photoperiod-sensitive millet cultivars, defining the growing cycle schedule, harvest dates and weighting factors (Alhassane (2009) and Dancette (1983)).

Antoine Leblois *et al.* (2011) have used a grid optimization process to maximize the objective function. The literature shows different objective functions such as the semi-variance (or downside risk as used in Vedenov and Barnett, 2004) or the mean-variance criteria. The former only takes a risk into account, without considering the average consumption level. It is thus useful in calibrating an insurance contract but is insufficient for assessing the farmers' utility gain from insurance when considering its implementation costs. They have finally retained the power or Constant Relative Risk Aversion (CRRA) utility function to compute certain equivalent income (CEI) and value the overall insurance gain. Power utility functions have the advantage of facilitating a comparison for different risk aversions.

The insurance gain is generally higher when dealing with the simulated crop growth phase than the observed phase. It validates the use of simulated growth phase for index-based insurance products in the case of photoperiodic crops. Taking the average value for each village leads to a mis-estimation of insurance gain when computed with a concave utility function that depends on income distribution and

sample size. The presence of village yield heterogeneity within the villages modifies the effective gain of insurance calibrated on village averages. It highlights the usefulness of calibrating insurance parameters on the observed yields at the plot level (Antoine Lebloiset *et al.*, 2011).

Selyaninov, (1958) (quoted in Bokusheva, and Raushan 2004) has suggested identifying drought by using an index accounting for the effects of two factors: precipitation and temperature. He introduced a hydro-meteorological coefficient (HTC) ($=10\sum R/\sum T$), where $\sum R$ is the cumulative precipitation in mm during the period with an average daily temperature $\geq 10^{\circ}\text{C}$; $\sum T$ is the sum of the average daily temperature in degrees Celsius in the same period. Selyaninov demarcated weak drought when HTC was ≥ 2 , a middle drought when $2.0 < \text{HTC} < 1.0$, and a strong drought when $1 \leq \text{HTC} \leq 0.5$. Ped(1975) (quoted in Bokusheva, Raushan 2004) suggested measuring of a drought by means of an index (S_i), which considers, in addition to precipitation and temperature, soil moisture also. Bova (quoted in Bokusheva, Raushan 2004), introduced a drought index by using the following formula: $K=10(W+R)/\sum T$, where W is the productive soil moisture in one-metre soil horizon during springtime, R is the cumulative precipitation from springtime until the moment of index assessment, and T is the sum of the average daily temperatures in the period, with an average daily temperature $\geq 0^{\circ}\text{C}$.

Bokusheva, (2004) have used all the three drought indices described above for developing a drought-index insurance product. To prove suitability of the selected indices in reproducing weather conditions in the individual years, their correlation coefficients with wheat yields for each of the 12 farms were calculated. The highest correlation coefficients were observed in the case of farms which were located in the weather station surrounding area.

Martin Odening *et al.*, (2007) have examined the rainfall variability and its implications for wheat production risk in northeast Germany. The hedging effectiveness of rainfall options and the role of spatial basis risk were analyzed using a daily precipitation model. Rainfall is a binary event and is much more erratic than temperature changes. Further, the correlation between rainfall amounts at the adjacent locations is relatively low. The sequence of wet and dry days follows an autoregressive process. This means that the probability of a rainy day would be higher if the previous day was wet.

The weather index considered by Berg *et al.*, (2009) is the cumulative seasonal (April–October) rainfall over the district. It is quite a simple index, since correlations between district yields and monthly rainfall totals were not strong. Since mathematical optimization can lead to unrealistic

solutions with frequent large payoffs and very high premiums, two constraints to the optimization to retain realistic solutions were added. First, a liquidity constraint that is the annual premium cannot exceed 20 percent of the farmer's mean income (without insurance). Two, the number of years with payouts must not exceed half of the total time series to meet the purpose of the insurance contract, i.e. it precisely compensates for the few worst years only. To account for the transaction cost for the insurer which increases with the frequency of payouts, the optimization was repeated with lower values (10 % for the liquidity constraint and a maximum average payout frequency of 25 %).

2.2. DESIGNING WEATHER INSURANCE CONTRACT

To reduce farmers' exposure to weather-related shocks, pay-offs from the weather insurance contract have to closely match the incurred losses. In this context, Goodwin and Mahul (2004) have pointed out that the designing of an efficient insurance contract depends on the relationship between the individual yield and the underlying weather index. Vedenov and Barnett (2004) have specifically emphasized the importance of the weather insurance parameters (tick size, strike, and limit) with respect to achieving hedging effectiveness, i.e. the degree to which weather risk is being reduced by an insurance product. Since then, formal models have been developed to determine the buyer's optimal choice of the insurance parameters with respect to risk reduction (quoted in Ines Kapphan, 2011).

Weather insurance pay-off functions have been designed by minimizing an aggregate measure of downside loss such as the semi-variance (Markowitz, 1991; Vedenov and Barnett, 2004). Vedenov and Barnett (2004) have derived the strike level by identifying the index level where the predicted yields corresponded to the long-time average. The remaining parameters were obtained by minimizing the semi-variance of loss assuming a linear relationship between the index and insurance payments (between strike and maximum payout) (quoted in Ines Kapphan, 2011).

Since information on future periods is not available, empirical studies extensively apply ex-post evaluation framework for index-based insurance product designing. Yet, if sufficiently long historical time series data are available, the *ex-ante* approach can be adapted by separating the historical data into two sub-samples or sub-periods. Consequently, the first sub-period can be used to specify the parameters of insurance contracts and to determine the optimal number of contracts to purchase. The data from the second sub-period provide the basis for ex-ante evaluation of the specified insurance contracts. Thus, the *ex-ante* framework seems to be more realistic, since it represents the actual

amount of information which a farmer can use to make a decision about the number of insurance contracts to purchase, and an insurer may use it to determine the insurance contract's parameters before selling the contract (Bokusheva and Breustedt, 2008).

Osgood *et al.* (2007; 2009) designed index-based weather insurance contracts for several African countries (Malawi, Tanzania, Kenya, and Ethiopia) that are implemented by the World Bank and Oxfam America under pilot projects. The contract design chosen by Osgood *et al.* allows optimization over piecewise linear contracts by minimizing the variance.

While designing index based weather insurance, after the selection of initial triggers and exits, preliminary contracts are tuned using a numerical optimization process performed on a WRSI based crop loss measure associated with the rainfall data. The objective function of this numerical tuning process is to minimize the variance in losses (lower the insurance payments) subject to the insurance price constraint. Because the final price of the contract is determined through negotiations between stakeholders, an unofficial "pseudo price" is used following standard and transparent risk pricing methods outlined in Osgood *et al.* (2007). The triggers of the contracts are the decision variables for the numerical tuner. In order to ensure the price does not go above the constraint, when the optimizer raises the level of one trigger, it lowers the levels of the others. Therefore, the task of the tuner is to determine the relative levels of the triggers (Osgood *et al.*, 2009).

The payout timing and correlation between payouts and losses are two performance indicators explained in details in Osgood *et al.*(2007). These methods of assessment are only the baseline in designing a robust contract, as contracts must also be made to address client needs. This typically requires manual adjustments to meet objectives that are not modeled in the tuning software. Triggers are often adjusted to round numbers to assist in ensuring that the farmer understands the appropriate level of precision reflected in the contract (Osgood *et al.*, 2009).

Every type of insurance is partial, with deductibles, limits, and items that are not covered.(With the relatively inexpensive product that index insurance is often chosen for, tough choices must be made in what is the most effective targeting of the partial coverage). The challenge of providing an affordable and effective insurance product is the challenge of building an index that targets the most important losses. The basic point behind insurance is not what is left uncovered, but that important risks are covered. Therefore, the elimination of features and payouts from contracts is not the end goal of a

contract design, but merely a part of the refinement. The identification and provision of the most important coverage is the central task (Osgood *et al.*, 2009).

2.3. STUDIES ON WEATHER INDEX INSURANCE

By using an "index" of weather observations as a proxy for crop loss, the problems of traditional indemnity insurance are either reduced or eliminated. This removes the subjective nature of insurance adjustment as well as the problems of adverse selection and moral hazard that are present in the traditional indemnity insurance model (Norton *et al.*, 2010).

Recently, weather derivatives have received considerable attention in the literature as potential risk management instruments for agricultural production (Skees, 2000; Skees *et al.*, 2001; Mahul, 2001; Martin, Barnett, and Coble, 2001; Miranda and Vedenov, 2001; Turvey, 2001a,b; Dischel, 2002) (quoted in Vedenov and Barnett (2004)). The major focus of these and other papers, however, has been on developing actuarially-fair pricing mechanisms for contracts and institutional frameworks that would be required to introduce weather-based insurance, especially in developing countries (Vedenov and Barnett, 2004).

Bokusheva and Breustedt (2008) have introduced an *ex-ante* evaluation concept into the analysis of index-based insurance effectiveness in the sense that insurance payments and optimal number of insurance contracts are determined based on the actually available information before purchasing insurance. They also conducted the common *ex-post* analysis to evaluate empirically the robustness of the results obtained by applying these two different approaches. They also compared the effectiveness of index-based insurance with a farm yield insurance by applying these two approaches.

There have been some rigorous attempts to provide meaningful methods to quantify risk for weather index insurance in a spatial dimension. Part of the complication is that weather index insurance (or weather derivatives) pricing according to 'burn cost' analysis deals not only with a spatial dimension but also a temporal one as historical frequencies are calculated. These calculations are further subjected to potential long-term trends due to the climate change, as well as variations due to the prevailing weather conditions according to the ENSO (El Nino Southern Oscillation) index (Norton *et al.*, 2010).

Norton *et al.* (2010) have contributed to the literature by offering a pricing strategy for both temperature and precipitation risks tailored to the specific typology of each type of risk. In many cases, the "portfolio" method of selecting a proportion of risk from each nearby station based on similarity in elevation (temperature) or geographic placement (precipitation) offers advantages over an index-based more sophisticated spatial statistics algorithms. Also, by compartmentalizing risk into the existing weather stations, the "portfolio" method has the advantage of allowing for easier pricing of policies for insurance and reinsurance companies. In this manner, they have demonstrated a strategy for pricing risk in distributed locations around the USA.

One approach to solve the problem of basis risk is to perform spatial analysis on weather data to provide a historical time series in varied geographic locations (Paulson and Hart, 2006). Another study intentionally analyzed the data from a flat area with consistent elevation (Richards, Manfredo, and Sanders, 2004). Other researchers have linked micro-insurance to microcredit and have advocated for a central financial institution to aggregate index insurance contracts so as to average out basis risk for all actors (Miranda *et al.*, 2010, Woodard and Garcia 2008). Clearly, if index insurance is to be widely used as a risk mitigation and climate adaptation tool for individual farmers, the problem of basis risk must be overcome (quoted in Norton *et al.*, 2010).

The study on efficiency of weather derivatives as primary crop insurance instruments by Vedenov and Barnett (2004) indicates that for the district crop combinations considered, weather derivatives may indeed provide fairly substantial decreases in risk exposure regardless of the criterion used. However, complicated combinations of weather variables must be used to achieve reasonable fits of the relationship between weather and yield. This makes contracts less transparent and may complicate marketing of the products to potential buyers. In addition, high predictive power of weather yield models does not necessarily translate into high performance of corresponding weather derivatives. They have suggested that any practical application of weather derivatives in agriculture will require an in-depth analysis for each crop-region combination under consideration.

Xiaohui Deng *et al.* (2006) have evaluated the efficiency of various index insurance products to reduce farm yield loss for representative corn farms in the southern Georgia. Index insurance products considered are based on county yields, cooling degree days (CDD), and predicted yields from a crop simulation model. This analysis tested whether a more sophisticated index insurance product based on

the 'Decision Support System for Agro-technology Transfer (DSSAT) crop production model would provide more risk reduction than simple products based on area yields or weather variables. Among the index insurance products, area yield index and DSSAT yield index products generally perform better than the CDD yield index insurance product.

Wonho Chung (2011) has compared the hedging cost and effectiveness of weather options with those of crop insurance for soybean and corn production in four counties of southern Minnesota. His analysis is consisted of four steps, viz. estimating the yield response models to observe the relationship between crop yield and weather variables for optimal weather hedge, estimating the weather process models to generate a statistical distribution of weather variables for pricing weather options, pricing the weather options to compare the hedging cost with that of using crop insurance and evaluating the hedging effectiveness as measured by several risk indicators (certainty equivalence, risk premium, Sharpe ratio, and value at risk) between using weather options and crop insurance.

Antoine Leblois *et al.* (2011) have mentioned different indices that could be used in weather index insurance, in their work on *ex-ante* evaluation for millet growers in Niger. They have tested the number of big rains (defined as superior to 15 and 20 mm) often quoted by farmers as a good proxy of yields, and the number of dry spell episodes in the season. Byun and Wilhite, (1999) have computed Drought Index on a decadal basis, and the Antecedent Precipitation Index has been computed by Shinoda *et al.*, (2000) on a closer area.

Fuchs and Wolff (2011) have argued that weather index insurance (WII) creates disincentives to invest in other non-insured crops, leading to potential overspecialization and monoculture; WII generates disincentives to invest in irrigation systems because farmers are insured only as long as production takes place on non-irrigated land; in the case of catastrophic events, food prices can potentially inflate with indemnity payments at the expense of the uninsured poor. A series of additional papers (Cai *et al.*, 2009; Giné and Yang 2009) (quoted in Alan Fuchs and Hendrik Wolff, 2011) have analyzed the determinants of participation of WII and found that the strong correlation between weather index and yield (i.e., the lower is the basis risk) is associated with a higher take-up rate of rainfall insurance.

An economic analysis of weather derivatives from the viewpoint of a potential buyer requires the solution of three interrelated problem areas: one, the statistical modeling of the relevant weather variables; two, the quantification of the relationship between the weather variables and the production;

and three, the development of a theoretically consistent pricing model. Oliver Musshoff *et al.* (2006) have focused on the first aspect and a daily precipitation model was specified, from which indices could be derived that determined the payoff of the derivative. Based on this model “fair prices” can be calculated, which constitute a lower bound for the value of a derivative.

By covering the risk of weather-induced crop failure, index insurance is often intended as a means to encourage farmers to adopt riskier but more productive farming practices, such as using high quality inputs. Therefore, a more accurate estimate of insurance benefit to the farmers should account for these factors, otherwise it will be an underestimate of insurance utility (Berg *et al.*, 2009).

Scientific evidence showing that climate change shifts the mean and variance of crop yields, is accumulating. The effect of changes in climatic variables on mean crop yields has been studied widely (Reilly, 2002; Deschenes and Greenstone, 2007; Schlenker and Roberts, 2009). Climate change thus makes agricultural production riskier (IPCC, 2001; IPCC, 2007), and without risk management less profitable. Consequently, agricultural insurance solutions become more important to protect against a climate change induced increase in weather-related losses (quoted in Kapphan *et al.*, 2012).

Kapphan *et al.* (2012) have analyzed the potential for weather insurance in the light of climate change. They have evaluated the benefits from hedging weather risk given that day’s climatic condition, and have compared them to the benefits from hedging weather risks with adjusted insurance contracts in a warming and more variable future climate. An adjusted insurance contract explicitly takes the expected changes in the mean and variability of both weather and crop yields into account. To design an adjusted weather insurance contract, they have used simulated (forward-looking) weather and yield data representing a possible climate change scenario. They have also assessed the effect on risk reduction from hedging weather risk in a changing climate with non-adjusted weather insurance contracts. Non-adjusted insurance contracts are designed using historical (backward-looking) data.

Kapphan *et al.* (2012) have selected four weather indices – single as well as multi-peril indices – that offer risk protection for different weather phenomena and vary in their goodness of fit and have found that with climate change, the effect of weather on corn yields increased. For example, for today’s weather condition, Index 2 explains 50.3 percent of corn yield variations, while with climate change, 68.3 percent of the variations are explained. For Index 3, the Spearman rank correlation coefficient increases from 46.3 percent to 67.8 percent with climate change. Overall, a larger fraction of corn

yields is explained by weather, which implies that the potential for hedging yield risk with weather-based insurance products improves.

The application of non-parametric and parametric methods has shown that results are alike, even if different distributions of the weather index are assumed. The extent to which the weather index insurance contributes to the risk reduction depends heavily on the insured crop and the location of the reference weather station. The risk reduction potential for corn production exceeds that of wheat production. The fact that wheat is highly dependent on irrigation during winter might explain the lower potential of the precipitation-based insurance (Heimfarth and Musshoff, 2011).

2.4. BASIS RISK

In an insurance context, basis is the difference between the loss incurred by the insured and the indemnity received. Basis can occur due to factors such as contract characteristics (e.g., deductibles or co-payments) or errors that occur in the process of establishing the sum insured or in conducting loss assessment. If basis is relatively small and predictable, as would be the case with a modest deductible, it is generally not a major concern for an insurance purchaser (Anonymous, 2010).

Variability in basis, or *basis risk*, on the other hand, can be a major concern and is the primary limitation of index insurance. Basis risk creates the possibility that indemnities will not be highly correlated with the losses of the insured. A source of basis risk is the imperfect relationships between the index, the cause of loss, and the loss (Anonymous, 2010).

Basis risk describes the precision with which the index can be used to estimate losses of the insured. It can be represented in part by the variance of the conditional distribution of losses given a specific value of the index. Because data are insufficient to capture the conditional distributions described above, practitioners have used correlations (or co-variances) between losses and the index to estimate basis risk. To better understand the primary sources of basis risk and relate these to product design, it is helpful to break down the covariance between the index and losses into two main components: (1) the covariance between the cause of loss and loss; and (2) the covariance between the index and the cause of loss (Anonymous, 2010).

Basis risk may take two basic forms in the context of weather index insurance. First, the “local” basis risk refers to the phenomenon by which observed weather variables do not correspond strongly with yield losses. It must be recognized that the weather is undoubtedly a factor in crop production, but must be considered simultaneously with other, often undetectable factors. Furthermore, stations with a dearth of useable data will experience difficulties in accurate pricing. The second type of basis risk is referred to as “spatial” basis risk, and refers to the spatial relationships of risk in a geographic area and the variance introduced at increasing distances from locations where the rainfall amount is measured (Norton, 2009).

Woodard and Garcia (2008) in their work on basis risk have examined the degree to which a particular weather derivative is an imperfect hedge against shortfalls for a given rainfall exposure. In this study, the underlying index on the weather derivative and the exposure being hedged correspond to the same geographic location.

Product (local) basis risk is measured as the difference between the percentage changes in the risk measure, i.e., root mean square loss (RMSL), for the hedged versus un hedged exposure. For example, a percentage reduction in RMSL of 100 percent would imply no local basis risk for the instrument, while ‘0’ percent would mean that the local basis risk of the instrument is high (Woodard and Garcia, 2007).

2.4.1. Spatial Basis Risk

Woodard and Garcia (2007) have categorized basis risk into three types: local, geographic, and product. Local basis risk refers to the gap between shortfalls for a given exposure and the payoffs of the hedging derivative, where the underlying index on the weather derivative and the exposure being hedged correspond to the same geographic location. Spatial basis risk happens by different geographic locations for hedging as defined above. Product basis risk refers to the difference in hedging effectiveness between alternative hedging instruments. They have suggested that while the degree of spatial basis risk may be significant, it should not preclude the use of geographic cross-hedging. They have found that the degree to which spatial basis risk impedes effective hedging diminishes as the level of spatial aggregation increases.

Berg and Schmitz (2008) have stated that spatial basis risk could probably be reduced substantially by utilizing the information of several surrounding weather stations instead of only the nearest one (quoted in Norton, 2009).

According to Wonho Chung (2011), spatial basis risk, which comes from the distance between the weather station for weather derivatives and the exposure location, needs to be controlled to make weather derivatives a more effective hedging instrument.

Odening, Musshoff, and Xu, 2007(quoted in Wonho Chung, 2011) have quantified the spatial basis risk by estimating the popular de-correlation function which represents the relationship between the correlation coefficient between the precipitation at different places and the distance between these places.

While a comparatively large amount of analysis has been expended on the local effects of basis risk, or more precisely the weather/yield relationship, very little analysis has been done about the geographic nature of basis risk, otherwise known as the uncertainty that develops as the distance from a known location increases. The traditional Geographic information system (GIS) methods of spatial interpolation like inverse distance weighting are ill-fitting for several reasons. The insurance payout is a function of temperature (or rainfall), but spatial interpolation methods bias the variability, and it is the variability that insurers, are most concerned with. Second, it is not so much the geographic or spatial relationships that are of interest, but the geographic or spatial relationships given certain weather conditions. In other words, the mean for a known location is only of value at that location, but we need to analyze the spread of risk in a distributed geographic area as different weather conditions prevailed on a year by year basis. The spatial interpolation method for solving this would presumably be to interpolate a map for each individual year of study and combine them to make a composite. This would provide a measure of risk at each location, but this would not, however, allow us to price payouts for unknown locations given a series of observations in future years (Norton, 2009).

According to Guenther Filler *et al.* (2009) the relationship between weather events at different locations is not only relevant while calculating joint losses from the view point of the insurer. It is also crucial for the hedging effectiveness of weather derivatives that insurance companies may wish to sell to farmers. It has been frequently stressed in the literature that the hedging effectiveness of weather derivatives is eroded by spatial basis risk (e.g. Woodard and Garcia, 2008).

Odening M *et al.* (2007) have analyzed the magnitude of spatial basis risk by means of a de-correlation analysis. The calculation of spatial basis risk was carried out for rainfall sum in June and rainfall deficit from April 1-June 30 using rainfall records for 23 weather stations in the Berlin and Brandenburg region from 1983 to 2003. The results revealed that the relationship between distance and correlation becomes less precise with increasing distance. Investigations on the relationship between spatial basis risk and hedging effectiveness also revealed that hedging effectiveness of a 'put' option is considerably reduced the farther away the producer is located from the reference weather station. They have suggested the inclusion of additional weather variables in the weather index (e.g. temperature or humidity) to mitigate the problem of basis risk.

Woodard and Garcia (2007) have defined spatial basis risk as the additional risk that arises by using a non-local contract. While spatial basis risk is defined in terms of a particular site, it is possible for location indices to be specified as a weighted set of locations to identify the effect of offsetting an exposure risk using weather derivatives from multiple non-local markets. A positive value of spatial basis risk implies that hedging with non-local as opposed to local contracts introduces extra basis risk. Negative values of spatial basis risk mean that the non-local derivatives are more effective hedging instruments.

The insurance's risk reduction potential over the observation period has been evaluated by Heimfarth and Musshoff (2011) by measuring changes in the standard deviation and the VaR of grain revenues with and without insurance. The spatial basis risk, which is inherent to the index insurance, has been quantified using a de-correlation function. Statistical evidence is provided up to which size of an area around a weather station the insurance can be provided for surrounding farms at the community level.

Quantification of the spatial basis risk using a de-correlation function reveals that the area around a reference weather station cannot be unbounded for standardized weather index insurance. Heimfarth and Musshoff (2011) have selected weather stations from a nearly homogeneous area and have found a significant correlation between the weather indices within a range up to 100 km around a weather station. The application of parametric approaches can remove the request of continually data updates of time series which can contribute to the expansion of the analysis.

2.4.2. Product Basis Risk

A study on weather index drought insurance by Berg *et al.* (2009) shows a negative correlation between rainfall and index/yield, *albeit* with a certain dispersion, even for low cumulative rainfall. Several factors can explain this dispersion. First, cumulative rainfall is not a perfect proxy for yields: for a given rainfall amount, intra-seasonal distribution can have significant effects on yields (Winkel *et al.* 1997). Moreover, rainfall is not the only climatic variable impacting yields: radiation and temperature also influence crop productivity. More generally, climate is not the only driver of crop production: non-climatic factors, for instance the occurrence of pests or farming practices (e.g., sowing date, use of fertilizers), can have significant impacts on yields. In addition, particularly for some vast districts, the locations of the rainfall stations may not correspond to the areas under cultivation, so that the rainfall index does not truly represent the climate experienced by the crops, resulting in weak correlations between rainfall and yields. Contracts over larger districts tend to provide a weaker increase in certain equivalent income (CEI). Finally, correlations on relatively short time series (21 years) are unstable. Each year has an important weight in the correlation coefficient. Hence any one-year mismatch between yields and rainfall, for one of the reasons mentioned above, can significantly reduce correlations and increase basis risk.

Berg *et al.* (2009) have found that the farmers' gain from an insurance contract is higher in the driest part of the country, which is more prone to droughts and exposed to crop failures. In the same way, among the different crops considered, corn and groundnut seemed to be the most suitable for implementing an insurance system since their respective yields show a large variance and a generally high correlation with the weather index.

2.4.3. Studies on Basis Risk

Basis risk may be reduced through the selection of appropriate weather observations to construct the index, but in reality, the prevailing weather conditions are only one variable in crop production and are often considered exogenous to the production function (Turvey and Norton, 2008). Basis risk is a major problem on using a risk-smoothing mechanism such as weather index insurance. If the product is not properly designed, the advantages of smoothing risk could be harmful to the farmers' bottom lines (Norton *et al.*, 2010).

Norton *et al.* (2010) have investigated basis risk using a novel approach to space measurement. They have developed a program that is linked to all the weather stations in a given region (i.e. includes data

on all weather stations in the United States). From a randomly selected point, they selected all weather stations within a prescribed radius and calculate the particular weather risk at each station to calculate the burn rate insurance premium. This was done for the same specific criterion for all stations within the sphere. First, they compared the premiums at each station to measure heterogeneity over space. Second, they compared on a year by year basis the payouts that would have been made at each pair of locations. Third, they measured the error or basis risk between each station pair and regressed the mean differences against a number of spatial variables. These spatial variables included longitude and latitude coordinates as well as elevation difference and distance between weather stations.

Paulson and Hart (2006) have while analyzing basis risk in the specific case of rainfall mentioned two components of basis risk. The recorded precipitation at the location of the weather station may not be highly correlated with actual precipitation at the farm, and production or revenue on the farm may not be highly correlated with precipitation at the farm. They focused on the first component of basis risk by utilizing a spatial kriging model to interpolate rainfall at locations where actual rainfall is not observed (i.e. the farm). The kriging results have also been compared with those obtained from a simpler inverse distance weighted (IDW) estimator for rainfall at unobserved locations. The second component of basis risk i.e. product basis risk has been addressed through the use of indemnity factors obtained through simple regression analysis relating losses to precipitation shortfalls. The insurance policy has been rated as an exotic option on rainfall using the historical rainfall data, the interpolation results, and Monte Carlo analysis assuming that rainfall at a given site follows the Gamma distribution.

Kriging or optimal prediction refers to the practice of making inferences on unobserved values of a random process given the data generated from the same process (Cressie). In practice, kriging techniques form a predictor which is equal to a weighted average of data in the sample. The weights used in the average are determined from the correlation structure of the process which may be given, assumed, or estimated from the data. Kriging techniques have been rigorously shown to provide predictors which are not only unbiased, but are also efficient linear estimators. In general, studies have shown that kriging dominates the simpler interpolation methods for areas with smaller sampling densities while the methods are fairly equivalent for areas with sampling grids of higher density (Paulson and Hart, 2006).

The actual take-up of index insurance unless heavily subsidized, is small in low income countries. Mobarak and Rosenzweig (2012) have examined whether the existence of informal insurance crowds out the market for formal index insurance in a context in which the index insurance product is subject to basis risk and have examined the effects of both informal risk-sharing and index insurance on risk-taking. They have shown in a simple model incorporating cooperative informal risk-sharing and index insurance subject to basis risk. When basis risk is present, however, informal risk sharing, by covering household losses that are the consequence of basis risk, enhance the benefits from formal index insurance contracts that permit increased risk-taking.

Using a combination of non-experimental and experiment-based survey data from rural India, Mobarak and Rosenzweig (2012) have found that basis risk, as measured by the perceived distance of the respondent to the nearest rainfall station, is a significant impediment to the take-up of the index insurance product. However, consistent with the model the negative effect of basis risk is attenuated for households in sub-castes that more successfully indemnify individual losses. Households in sub-castes that already informally provide insurance coverage based on aggregate shocks on the other hand are less likely to purchase the index product. Thus, their findings indicate that informal insurance is both a complement to formal index insurance and a substitute, depending on basis risk and the nature of the informal insurance arrangement.

2.5. WEATHER DATA ANALYSIS AND CLIMATE TRENDS

Rajeevan (2001) highlighted that there was no trend in monsoon rainfall if the country is taken as one unit, though, the trends (increase or decrease) do vary on a regional scale. Similar observations were reported by Rupa Kumar *et al.* (2002). However, Prasad Rao and Gopakumar (2011) reported that the monsoon rainfall over the country has increased by 44.8 mm (0.23 mm per year) over a period of 194 years, from 1813 to 2006. The trend analysis of rainfall data from 1140 meteorological stations carried-out at the Central Research Institute for Dryland Agriculture (CRIDA) has shown a negative trend among the stations situated in deep southern part, southern peninsular, central India, parts of north Indian region and north-eastern regions. Positive deviations are seen at Gujarat, Maharashtra, coastal Andhra Pradesh, Rayalseema and Odisha. However, part of the country comprising the areas in central parts covering eastern Uttar Pradesh, eastern Madhya Pradesh, west coast and greater parts of North West India have not shown any changes. Among the districts, 40 percent stations have shown a negative trend, 48 percent a positive trend and 12 percent have depicted no change in rainfall (Rao *et*

al., 2010)⁸. Jain and Vijay Kumar (2012) have indicated that the monsoon rainfall has increased over the six river basins while decreased over 16 river basins across the country. A marginal decrease has been noticed over the Ganga basin, and it was significant in the Indian basin and the west-flowing river from Tapi to Tadri. Parthasarathy and Dhar (1974), Subbaramayya and Naidu (1992), Singh and Sontakke (2002), Ramesh and Goswami (2007), Pattanaik (2007) and Krishnakumar *et al.* (2009) are among others who have studied variations in monsoon rainfall across the country in details.

Depending upon the data points and data periods used, all the studies on monsoon rainfall have revealed that regional and location-specific trends are evident (increasing or decreasing). The analysis of monsoon rainfall variations/trends for the country as a whole did not depict any specific trend. However, since WI product is designed largely for micro locations (sub-district or lower), it is suggested to consider location-specific rainfall information.

Studies by various authors (Dash *et al.*, 2007; Sinha and Srivastava, 1997; Goswami *et al.*, 2006) have shown that, in general, the frequency of more intense rainfall events in many parts of Asia has increased, whereas the number of rainy days and the total annual precipitation has decreased. The increase in intense rainfall events leads to more severe floods and landslides.

A decrease in the amount of rainfall, particularly for stations in the hilly terrain, was found in annual extreme rainfall over Kerala (Soman *et al.*, 1988). Rakhecha and Soman (1994), while analyzing the extreme events of one to three days duration at 316 stations across India for the period 1901 – 1980, had found that the increasing trends in these events were not statistically significant at most stations. They reported that the extreme rainfall series at stations over the West Coast north of 12 degrees N and at some stations to the east of the Western Ghats over the central parts of the peninsula, showed a significant increasing trend at 95 percent level of confidence. Some stations over the southern peninsula and the lower Gangetic valley have exhibited a decreasing trend at the same level of significance.

Sen Roy and Balling (2004) have analyzed the daily rainfall data for 1910 – 2000 at 129 stations and found an increasing trend in a contiguous region extending from the north-western Himalayas in Kashmir through most of the Deccan Plateau in the south and decreasing values in the eastern parts of

⁸Rao, GGSN, Rao, AVMS, Vanaja, M., Rao, VUM and Ramakrishna YS.(2010). Impacts of regional climate change in India. (13-42 pp).In: *ClimateChange and Agriculture over India* (Eds.).GSLHV Prasada Rao, GGSN Rao and VUM Rao.PHI Learning (P) Ltd., New Delhi.328 p.

the Gangetic Plains and parts of Uttarakhand. Trends in extreme rainfall indices for the period 1901 – 2000 were examined for 100 stations over India by Joshi and Rajeevan (2006). Most of the extreme rainfall indices for the South West monsoon season and annual period showed significant positive trends over the west coast and north-western parts of the peninsula. However, two hill stations (Shimla and Mahabaleshwar) showed a decreasing trend in some of the extreme rainfall indices.

Using high resolution daily gridded rainfall data for the period 1951 – 2003, Goswami *et al.*, (2006) have shown that there were significant increasing trends in the frequency and magnitude of extreme rain events over central India during the monsoon season. They have also found a significant decreasing trend in the frequency of moderate events during the same period, thus leading to no significant trend in the mean rainfall. The results of this study were significant for some places when analysis was performed at a finer resolution (1 ° latitude and 1 ° longitude) by Ghosh *et al.* (2009).

The variability and long-term trends of extreme rainfall events over central India were examined by Rajeevan *et al.* (2008) using 104 years (1901–2004) data of high-resolution daily gridded rainfall. They have found a statistically significant long-term trend of 6 percent per decade in the frequency of extreme rainfall events. According to them, the increasing trend of extreme rainfall events during the past five decades could be associated with the increasing trend of sea surface temperatures and surface latent heat flux over the tropical Indian Ocean.

Pal and Al-Tabbaa (2009) have studied the trends in seasonal rainfall extremes in Kerala, using gridded daily data for 1954–2003. They have found winter and post-monsoon extreme rainfall having an increasing tendency with statistically significant changes in some regions and decreasing trends in spring seasonal extreme rainfall. They have also studied the changes in frequency and magnitudes of extreme monsoon rainfall deficiency and excess from 1871 to 2005 over five regions in India. The extreme monsoon seasonal precipitation exhibited a negative tendency, leading to an increasing frequency and magnitude of monsoon rainfall deficit and decreasing frequency and magnitude of monsoon rainfall excess.

The long-term trend in monsoon season's extreme rainfall events for 1951–2005 was analyzed by Pattanaik and Rajeevan (2010). The average frequency of extreme rainfall events along with the contribution of extreme rainfall events to the seasonal rainfall has shown a significant increasing trend (above 98% confidence level) over India during monsoon season and also during June and July. It has

also been found that the increasing trend of contribution from extreme rainfall events is balanced by a decreasing trend in low rainfall events.

Kothawale *et al.* (2010) have studied the association between El Niño Southern Oscillation (ENSO) and monsoon rainfall over India and have reported a strong association between El Niño events and deficient monsoon rainfall. Nearly 60 percent of major droughts over India have occurred in association with El Niño events. Strong association between monsoon droughts and El Niño events was noted by other authors too. On the other hand, La Niña events were associated with more rainfall during monsoon and cooling. Earlier, Krishna Kumar *et al.* (1999) had shown that the relation between the Indian monsoon and ENSO weakened in recent decades.