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WEATHER DERIVATIVES REVISITED

A DISCOURSE ON SCALABILITY, FEASIBILITY AND SUSTAINABILITY

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Abstract

Over the last decade, weather derivatives have been offered in developing countries to mitigate weather risk in agriculture, but the demand remains low. Chapter One explains this demand anomaly by decomposing an insurance seeker's motivation into three summands. The first summand discusses the effect of contractual non-performance due to basis risk, the second one discusses the effect of subsidies and the third one discusses the effect of adverse selection on motivation to purchase weather derivatives.

Chapter Two analyses the basis risk of wind indexed weather derivatives for Typhoon risks of rice farmers in the Philippines. A regression analysis could not reject the null hypothesis that wind speed does not affect rice yields. Resultant high basis risks lead to mitigation of risk through diversification and not indemnification.

Chapter Three introduces pay-off period as a factor for frequent post-pilot discontinuation of weather derivatives. The discounted pay-off period and loss ratio are introduced as important decision variables for insurers, in deciding the loan or grant parameters as well as quota share reinsurance parameters. Restructuring the pilot programmes as well as coupling weather derivatives with micro-loans have been recommended.

Chapter Four introduces the case of inter-temporal adverse selection in weather derivatives. Farmers might base their insurance purchase decisions on weather outcomes of prior months. Thereof resultant financial repercussion of adverse selection on the insurers' reserve has been estimated. Additionally, a method to identify the source of this information asymmetry has been proposed. This helps the insurer decide whether to restructure the product and when to initiate the contract.

Weather derivatives are necessary proxies to traditional crop insurance. This dissertation makes theoretical as well as empirical contributions towards a growing literature on weather derivatives and its participation pattern. The goal is to help policy makers and insurers make better designs and decisions so that weather derivatives can perform efficiently as tools of poverty alleviation by hedging weather related risks in agriculture.

Kurzfassung

In den letzten Jahrzehnten wurden Wetterderivate in Entwicklungsländern angeboten, aber die Nachfrage ist nach wie vor verhalten bis nicht existent. Kapitel eins erklärt diese Diskrepanz. Der erste Abschnitt diskutiert die Auswirkung des Basisrisikos, der zweite Teil den Einfluss einer Subventionierung und der dritte Abschnitt klärt die Auswirkung der adversen Selektion auf die Kaufbereitschaft.

Kapitel zwei analysiert das Basisrisiko von Wind index-basierten Wetterderivaten für Taifun-Risiken von philippinischen Reisanbauern. Die durchgeführte Regressionsanalyse konnte die Nullhypothese, dass "Windgeschwindigkeit keinen Einfluss auf den Reisertrag hat" nicht vollständig widerlegen. Die angebotenen Produkte führen durch Diversifikation und nicht durch Kompensation der Taifunschäden zu einer Risikominderung.

Kapitel drei diskutiert die lange Amortisationsdauer als einen der möglichen Gründe dafür, dass Wetterderivate nach einer Pilotphase nicht fortgeführt werden. Die Amortisationszeit und die Schadensquote werden als wichtige Entscheidungsfaktoren für Kredit- und Beihilfe-Parameter sowie "Quota Share" Rückversicherungs-Parameter vorgestellt. Abschließend werden Möglichkeiten für die Restrukturierung der Pilotprogramme sowie die Kopplung der Wetterderivate mit Mikrokrediten diskutiert.

Kapitel vier beschäftigt sich mit der Möglichkeit einer temporalen adversen Selektion bei Wetterderivaten. Landwirte können ihre Versicherungsentscheidungen auf die Wetterlage der vorangegangenen Monate gründen. Eine Schätzung der Auswirkungen der daraus resultierenden adversen Selektion auf die Finanzrücklagen der Versicherer wird dargestellt und eine Methode, die es dem Versicherer ermöglicht den optimalen Zeitpunkt der Kontraktschließung zu identifizieren, wird diskutiert.

Wetterderivate stellen, trotz ihrer Mankos, wichtige Risikomanagementinstrumente dar. Die vorliegende Dissertation liefert sowohl einen empirischen als auch einen theoretischen Beitrag. So werden unter anderem Vorschläge gemacht, wie Wetterderivate mit deutlich verbesserten Merkmalen angeboten werden können, die dann in der Lage sind, ihre Aufgabe als Instrument zur Verringerung wetterbedingter Risiken in der Landwirtschaft zu erfüllen.

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List of Abbreviations

Acronym	**Full form**
AIC	Akaike Information Criterion
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
BAAC	Bank for Agriculture and Agricultural Cooperatives, Thailand
BIC	Schwarz- Bayesian Information Criterion
CRRA	Constant Relative Risk Aversion
DARA	Decreasing Absolute Risk Aversion
ENSO	El Niño Southern Oscillation
FAO	Food and Agricultural Organisation
FAOSTAT	Food and Agricultural Organisation Statistical Database
FCIC	United States Federal Crop Insurance Corporation
FCV	Flue Cured Virginia
GDP	Gross Domestic Product
GIS	Geographic Information System
IBRTP	Index Based Risk Transfer Products
IFRS	International Financial Reporting Standards
INETER	Instituto Nicaragüense de Estudios Territoriales
INISER	Instituto Nicaragüense de Seguros y Reaseguros
MFI	Micro Finance Institution
MPCI	Multiple Peril Crop Insurance
NLS	Non-Linear Least Squares
NPV	Net Present Value
OGP	Original Gross Premium
PCIC	The Philippine Crop Insurance Corporation
PPP	Purchasing Power Parity

Chapter 1

Deducing the Demand

1.1 An introductory discourse

Weather derivatives may be generalized as forward contracts, and they normally appear as futures or options. Although different kinds of future transactions are possible, options dominate the market as they are particularly appropriate to reduce downside risk. Since weather derivatives are applied as risk management instruments in enterprises such as agriculture, where downside risk is of great importance, this property of options comes in handy. In case of options, the buyer (long position) purchases a right and pays a premium for it, while the seller (short position) accepts the obligation and receives the premium. Options are further differentiated on the basis of this right into call options (where the buyer purchases the right to buy an underlying at a certain strike price, at a certain time) and put options (where the buyer purchases the right to sell the underlying at a certain price and time[1]). (Berg et al., 2006)

1.1.1 Terminology

Instead of referring to these products as weather derivatives or otherwise, Skees and Barnett (2006) refer to them as Index based risk transfer products or IBRTP since, they argue, structurally they are open-ended. In the economic literature, they take the form of contingent claims. However, in the legal and regulatory environment, they can either be structured as insurance or derivatives. In developing countries, where derivative markets are unlikely to be properly regulated, they are commonly structured as insurance products. However, this is contested in various other fronts. In most developing countries these products don't have any formal legal standing. For example, in India (with ˜30 million farmers insured with index insurance) the legal position of weather index insurance is uncertain – regulators have not clarified its position. According to Clarke (2011, p: 3), "Accountants have recently revisited the specific question of how to classify weather derivatives as part of the process of developing the International Financial Reporting Standards (International Accounting Standards Board 2007, pp: 450-451). IFRS contains a principles-based distinction between an insurance contract 'in which an adverse effect on the policyholder is a contractual

[1] European options can be only exercised at maturity. American options can be also exercised prior to maturity.

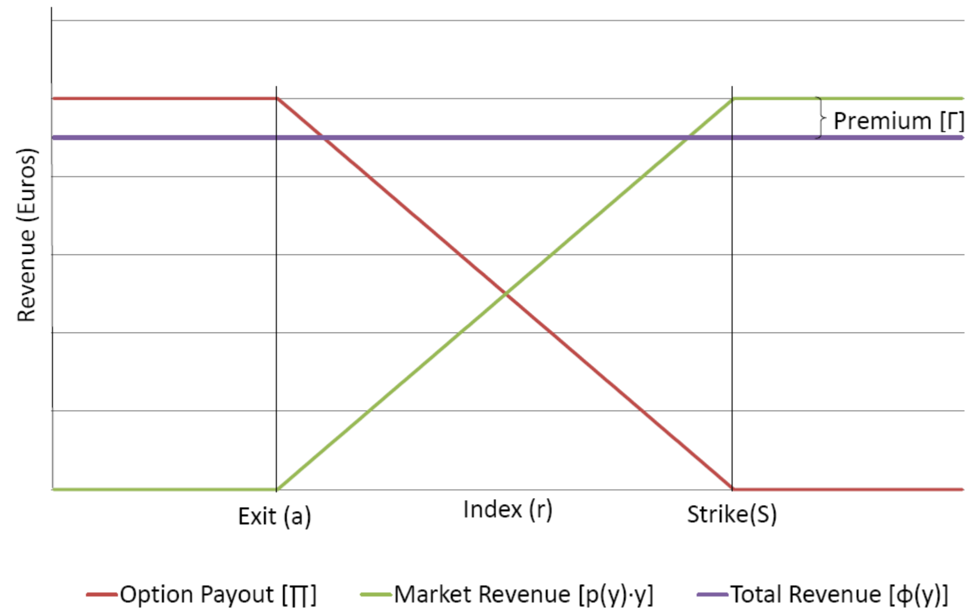
precondition for payment', and a derivative contract in which it is not. Under this definition, a weather derivative is a derivative, not any kind of insurance. A weather derivative is also classed as a derivative under US Generally Accepted Accounting Principles." Lawyers are also unsure about the legal form as reflected in the reports of Richard Carpenter in Murphy et al. (2011). Hence for the purpose of this body of work, these products and all variants thereof will be referred to simply as **Weather Derivatives**.

1.1.2 Description

The underlying of a weather derivative being weather parameters, is not directly connected with financial or commodity markets. These underlying are weather indices like temperature, precipitation, solar radiation or wind velocity, which are neither storable nor tradable and therefore represent so called "exotic underlying" (Schirm, 2000). In case of an agricultural weather derivative, indices are often designed based on specific crop or livestock yields, as they are affected by particular weather variables like temperature or precipitation. The payout is then calculated on the basis of the values these indices assume, which is in turn derived from the value of the relevant weather variables reported objectively by an independent weather station.

A stylised depiction of the revenue of a farm hedged with a weather derivative based on an index which is perfectly correlated with the actual loss is shown in Figure 1.1.1.

Figure 1.1.1: Revenue with weather derivative and no basis risk



Source: Own illustration.

As seen in the graph, to derive the revenue of a farm enterprise hedged with weather derivative $[\phi(y)]$, the yield $[y]$ is assumed to be a function of the weather parameter represented by the index $[r]$. The Exit point is the value of the index $[r]$ at which the yield $[y]$ equals the intercept $[a]$. This is the point where the crop is assumed to be entirely destroyed, the market revenue is at its minimum and the option payout at its maximum. In this stylised case $a = 0$, although for a general case the yield is assumed to be a function of x, such that $x = \max(a, r)$. The production function is therefore assumed to be Leontief-type production function (Berg and Schmitz, 2008) given by Equation 1.1.1, whereby y increases linearly with the values of x, with a slope b, until it reaches its expected maximum $\hat{y}_{max}$, such that:

$$y = \min\left[(a + bx), \hat{y}_{max}\right] + e_B \tag{1.1.1}$$

where, the error term $[e_B]$ is assumed to be normally distributed with zero mean and standard deviation of σ_{e_B}. In addition to that, a weather derivative is characterised by a Strike value $[S]$ and a tick value $[T]$. S corresponds to the amount of rainfall or the value of x which leads to $\hat{y}_{max}$, such that:

$$S = \frac{\hat{y}_{max} - a}{b} \tag{1.1.2}$$

and T is the payout per missing unit of x, such that:

$$T = b \cdot p_y \tag{1.1.3}$$

where, p_y is the unit price of the crop, assumed to be taken as given and not a stochastic variable. Such that the option payout (Π) is:

$$\Pi = T\left[\max\left\{0, (S - x)\right\}\right] \tag{1.1.4}$$

Therefore, the revenue without derivative is simply $p_y \cdot y$, which can be rewritten as:

$$p_y \cdot y = p_y\left[\min\left\{(a + bx), \hat{y}_{max}\right\} + e_B\right] \qquad (from\, 1.1.1) \tag{1.1.5}$$

and the revenue with derivative $[\phi(y)]$, is the sum of the market return (Equation 1.1.5), the option payout (Equation 1.1.4) subtracting the premium $[\Gamma]$, such that:

$$\begin{aligned}
\phi(y) &= p_y\left[\min\left\{(a+bx), \hat{y}_{max}\right\}+e_B\right] \\
&\quad +T\left[\max\left\{0,(S-x)\right\}\right]-\Gamma \\
&= p_y\left[\min\left\{(a+bx), \hat{y}_{max}\right\}+e_B\right] \\
&\quad +p_y\cdot b\left[\max\left\{0,(S-x)\right\}\right]-\Gamma \qquad (from\, 1.1.3) \\
&= p_y\left[\hat{y}_{max}+\min\left\{a+bx-(a+bS),0\right\}+\max\left\{0,b(S-x)\right\}+e_B\right] \\
&\quad -\Gamma \qquad (from\, 1.1.2) \\
&= p_y\left[\hat{y}_{max}+\min\left\{b(x-S),0\right\}+\min\left\{0,b(x-S)\right\}+e_B\right]-\Gamma \\
&= p_y\left[\hat{y}_{max}+e_B\right]-\Gamma \qquad (1.1.6)
\end{aligned}$$

At this point it is clear that the total revenue is independent of the index, exit, strike or tick value, instead it is dependant on e_B, which may be introduced as the Basis. It assumes the aforementioned properties of being normally distributed with zero mean $[E(e_B)=0]$ and the standard deviation $[\sigma_{e_B}]$ of the basis is the Basis Risk, discussed at length in the next chapter. Therefore, if a farmer buys a weather derivative, the payout should compensate the loss of revenue (before deducting the premium paid for the derivative), and ensure reduced variance in her revenue, provided the index correctly reflects the actual loss.

1.1.3 Timeline

Weather derivatives were first conceptualised when Aquila Energy structured a dual-commodity hedge for Consolidated Edison Inc., in July 1996 (Nicholls, 2004). By 1997 weather derivatives started to be traded over-the-counter. As early as 1999, weather derivatives were discussed in academic papers as tools for mitigating weather related risk in agriculture in developing countries (Bryla and Syroka, 2007). In 2002, international development organisations started piloting these products in developing countries some of which have been tabulated in Table 1.1.1 on page 8.

In this table, the country, the year of initiation, the target group(s), the coordinating organisation and the type of index have been tabulated. Most significant player in this arena was the World Bank's Agricultural Risk Management Team (erstwhile Commodity Risk Management Group), they in addition to their price risk management work in commodity markets, got involved in piloting weather insurance with funds from the Dutch and Swiss Governments.

The commonly adopted model is one of technical and financial assistance to established insurance providers in target countries, to demonstrate or assess the effectiveness of these derivatives. The first weather derivative transaction was piloted in India in June 2003, which was also the first-ever weather insurance project in the country. Since then there have been several other pilots around the world, including the ones in Ukraine, Ethiopia, Malawi, Kenya, Tanzania, Thailand and Central America (Bryla and Syroka, 2007). Experiences regarding the sustainability of these projects have brought forward different issues, but before delving into them, it is necessary to discuss the motivation of the international development community behind promoting these products.

1.1.4 Motivation

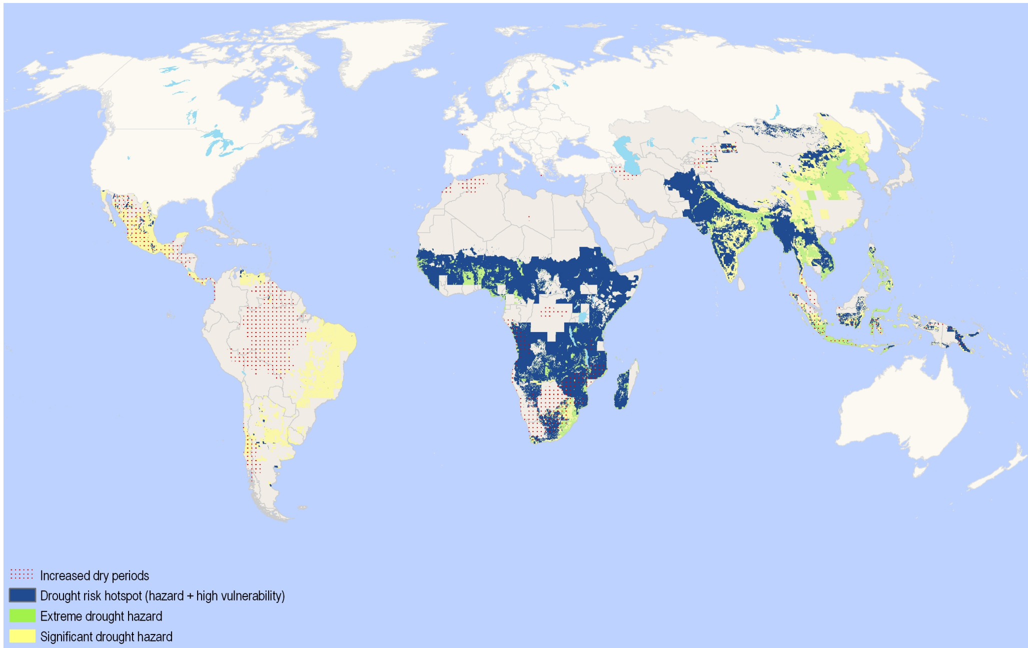
Developing countries mostly lie in regions of high weather related risk. As seen in Figure 1.1.2, South and Southeast Asia, and Sub-Saharan Africa are significant hotspots not only for drought occurrences but also on a scale of vulnerability resulting from drought.

Global Climate change is showing its starkest effects through deserts engulfing erstwhile cultivable tracks. A look at Figure 1.1.3 shows that the regions of highest risk of desertification lie in Asia Minor, Middle East and Sahel regions. Most countries in these regions are developing and low-income, house some of the poorest communities, and have dysfunctional or rudimentary economic buffer mechanisms.

Table 1.1.1: Forms of weather derivatives in different developing countries

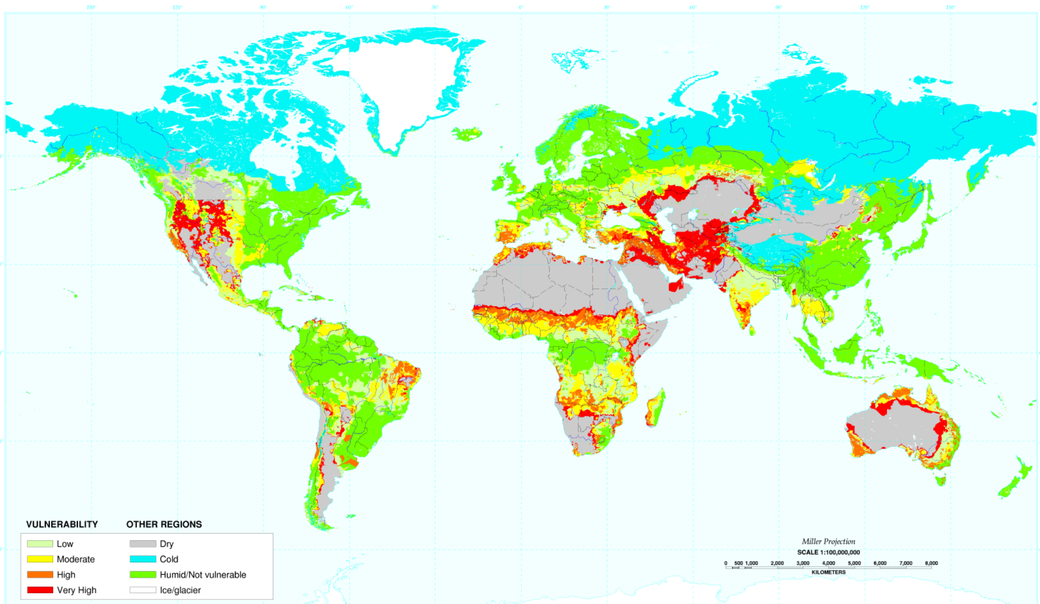
Country	Year	Participants	Coordinating organisation	Index	Source
India	2003	Smallholders	BASIX, ICICI Lombard	Rainfall index	Cole et al. (2013)
Malawi	2004	Maize, groundnut farmers	World Bank	Rainfall index	Giné and Yang (2009)
India	2004	Smallholders	Agricultural Insurance Company	Rainfall and temperature index	Burke et al. (2010)
Mongolia	2006	Herders	Index Based Livestock Insurance Project	District average livestock losses	Hellmuth et al. (2009)
Thailand	2007	Smallholders	Bank for Agriculture and Agricultural Cooperatives	Rainfall index	Hellmuth et al. (2009)
Millennium Villages (Kenya, Ethiopia, Mali)	2007	Smallholders	Millennium Villages	Rainfall and satellite based greenness index	Hellmuth et al. (2009)
India	2007	Potato contract farmers	Pepsico	Temperature and humidity index	Hellmuth et al. (2009)
Ethiopia	2007	Teff and bean farmers	HARITA	Rainfall index	Burke et al. (2010)
Nicaragua	2008	Smallholders	World Bank	Rainfall index	Burke et al. (2010)
Malawi	2008	Maize, tobacco farmers	MicroEnsure	Rainfall index	Hellmuth et al. (2009)
Tanzania	2009	Smallholders	MicroEnsure	Rainfall index	Burke et al. (2010)
Rwanda	2009	Smallholders	MicroEnsure	Rainfall index	Vargas and Torrero (2009)
Kenya	2009	Maize, wheat smallholders	Kilimo Salama	Rainfall index	Burke et al. (2010)
Kenya	2009	Smallholders	Rockefeller	Rainfall index	Burke et al. (2010)

Figure 1.1.2: Map of drought risk



Source: Ehrhart et al. (2009a).

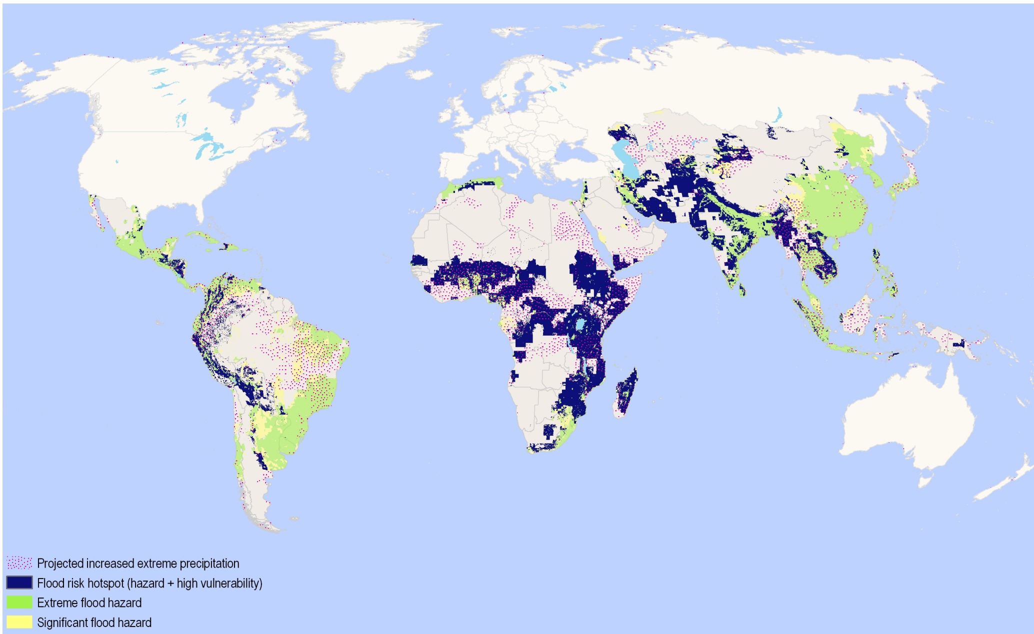
Figure 1.1.3: Map of desertification risk



Source: USDA (1998).

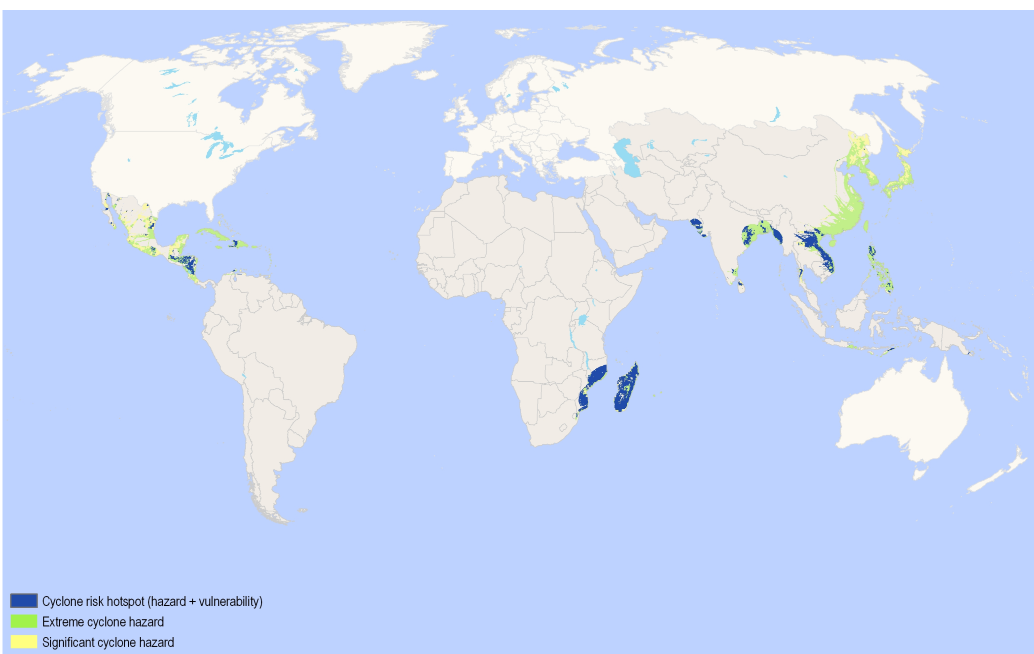
Aggravating the situation, the aforementioned regions are also top on list of flood risk and resultant vulnerability, as seen in Figure 1.1.4. The convergence of these factors makes agriculture in these regions a risky enterprise.

Figure 1.1.4: Map of flood risk



Source: Ehrhart et al. (2009b).

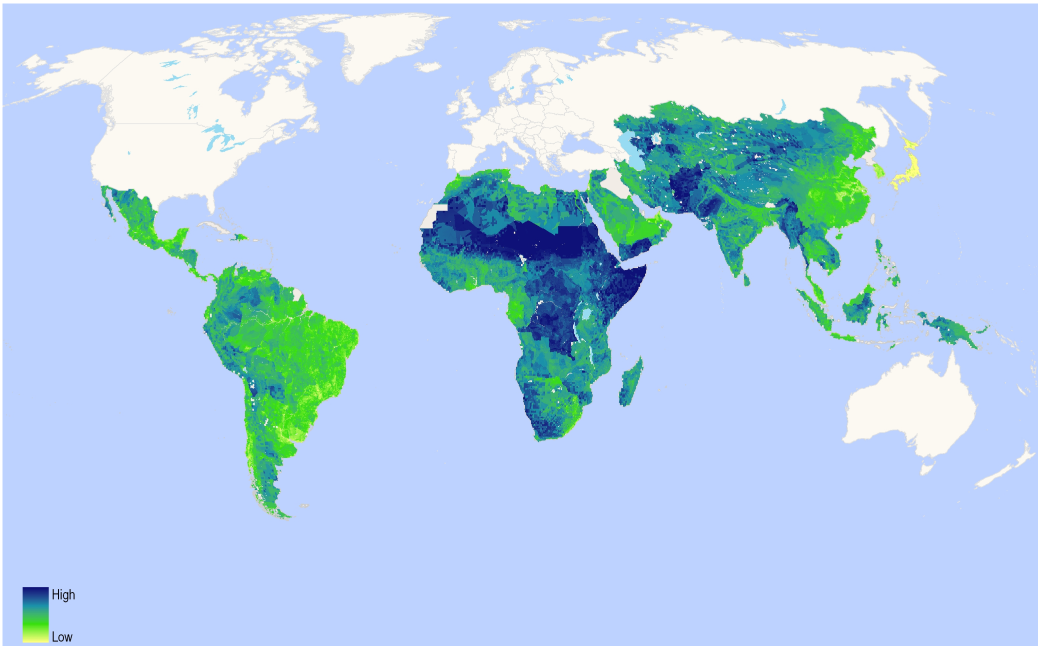
Figure 1.1.5: Map of Cyclone risk



Source: Ehrhart et al. (2009c).

The map in Figure 1.1.5 shows that the regions which are hotspots of cyclone incidence. Coincidentally, these regions are also inhabited predominantly by rice growing agrarian societies (detail discussion on this issue is to be found in the next chapter).

Figure 1.1.6: Vulnerability map

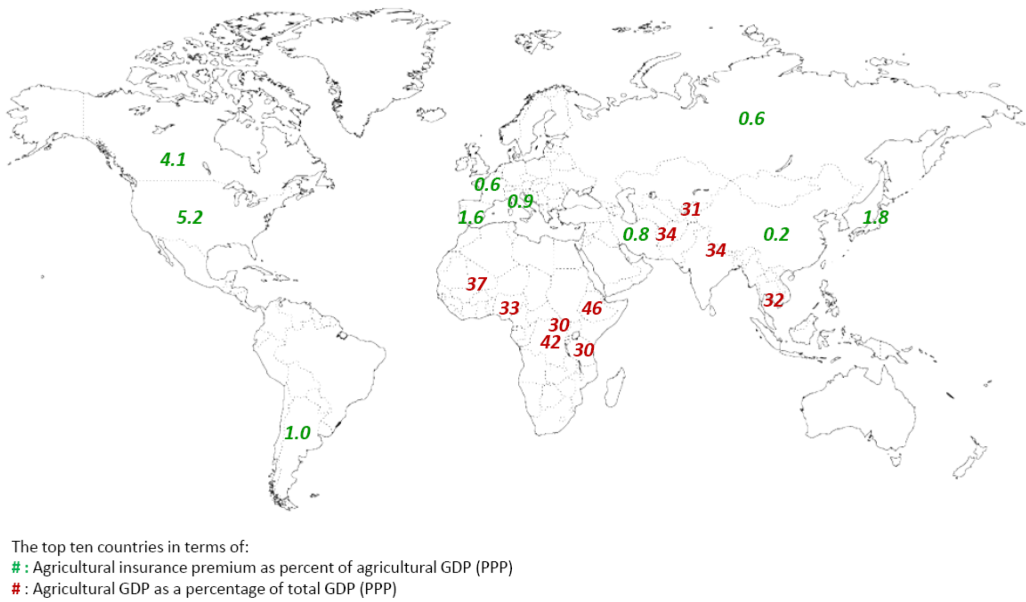


Source: Ehrhart et al. (2009d).

To sum up, Figure 1.1.6 shows the overall vulnerability. These regions are home to some of the poorest agrarian communities on earth and weather variability resulting from drought, desertification, floods and cyclone render them economically vulnerable.

Vagaries of weather may be considered as one of the most predominant risk to agriculture in developing countries. According to World Bank estimates, 1.29 billion people were living under $1.25 a day in 2008 (WB, 2012b). 70% of the poor living in rural areas depend on agriculture as their main source of income and employment (WB, 2012a). Risks in agriculture have detrimental effect on their economic well-being. Binswanger et al. (1993) find that with limited means to insure consumption in the face of an income shock, many households reduce risks at the expense of lower expected average outcomes or even higher risk to life and property. For example, farmers in riskier environments in South India choose asset portfolios less sensitive to rainfall variation despite the fact that they are less profitable.

Figure 1.1.7: Market potential for Agricultural Insurance



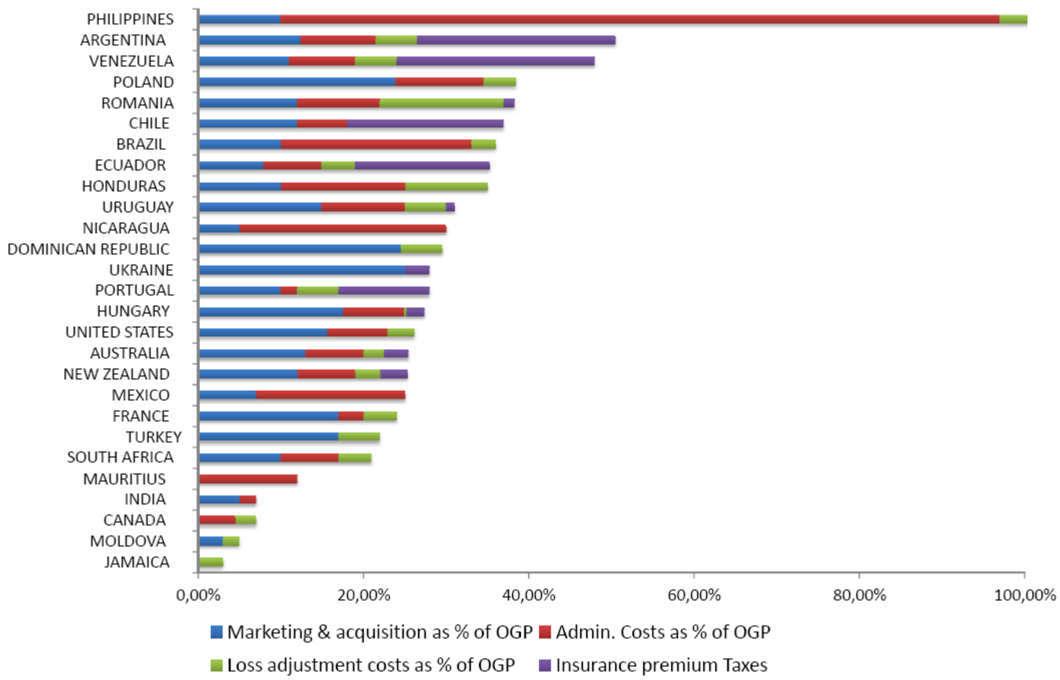
Source: Own illustration based on data from WB (2007); Mahul and Stutley (2010).

Logic dictates that agricultural insurance should be promoted in these regions, Figure 1.1.7 cements the point. If agricultural GDP as a percent of total GDP is taken as an indicator for the importance of agriculture in a country, the top ten figures intersect with the developing regions of the world. However, if agricultural insurance premium as a percent of agricultural GDP is taken as an indicator of how developed the agricultural insurance market is, the top ten figures lie completely in the industrialised regions, with a happy deviance in case of Iran and Argentina. The aforementioned arguments cumulatively indicate the growth potential of weather based agricultural insurance in the developing world.

The alternatives to weather derivatives are named-peril or multi-peril insurance policies which indemnify losses to one's property or crops from specific adversities or wide variety of events respectively (Edwards, 2003). A classic example of named peril insurance in agriculture is the hail insurance common in Europe. Both named and multi-peril insurances are predominantly available in developed countries.

The inherent limits to the development of markets for these insurances in the developing countries are: moral hazard, adverse selection, underdeveloped infrastructure, and covariate nature of weather events (these factors are discussed at length on page 54). In addition to that is the cost of delivering insurance. As seen in Figure 1.1.8 the costs expressed as percent of Original Gross Premium (OGP)[2] is arguably high in developing countries as compared to their industrialised counterparts. The reasons might be lacking infrastructure, low levels of financial education, which might push up the loss adjustment, and marketing and acquisition costs. This is a question warranting further research, and beyond the scope of this work.

Figure 1.1.8: Cost of delivering insurance in selected countries



Source: Own illustration based on Mahul and Stutley (2010, Annex E).

However, three things are clear from the previously presented information and analysis. Firstly, developing world needs weather related insurance to transfer the imminent risks from agricultural enterprise. Secondly, the solution has to be resilient to moral hazard and adverse selection to some extent and thirdly, it needs to be cost effective in terms of delivering these services. A careful look at the Figure 1.1.8 will prompt the reader that cost cutting is mostly required in the administrative and loss adjustment front.

[2]Original Gross Premium is the amount payable by the insured to the insurer, including the technical premium, to cover expected losses and catastrophe losses plus commercial loadings to cover marketing and acquisition costs, administration and operating expenses, and profit margin (Mahul and Stutley, 2010).

A novel solution is hence an insurance indexed to an objective indicator of weather, such as rainfall or temperature. Since weather is not affected by individual behaviour, and there is no asymmetry of information regarding occurrence of weather events (an exception is discussed in Chapter Four), weather derivatives are resilient to both moral hazard and adverse selection. Furthermore, since payouts are determined on the basis of weather data from independent meteorological stations, monitoring and loss adjustment costs are minimised (Barnett et al., 2008). Owing to these advantages, international development organisations started pro-actively promoting them in developing countries.

1.2 The Problems

Despite the arguments presented in the previous section, scores of pilots (please refer to Table 1.1.1 for a selection of projects) present an anomalous fact. Participation in weather derivatives is low in developing countries. This is an anomaly which seems to be beyond expectation of implementing agencies, since they went about promoting these products (as seen in Table 1.1.1). This dissertation endeavours to elucidate that anomaly. This anomaly has been identified and researched at length, and the different factors contributing to it have also been discussed in different papers. For example, Giné et al. (2008) point out the fact that farmers seldom experiencing payouts is an important factor (their paper finds that in only 11% of cases there is a payout for farmers in India). This fact is corroborated in the findings of Garrido and Zilberman (2008), where they find payouts in previous years to be an important factor influencing insurance purchase in the subsequent years among Spanish farmers. This low payout statistic adversely affect the trust of farmers in the insurance system (Giné et al., 2007), a fact also discussed by Cole et al. (2013). Cole et al. (2013) also find that demand for these products exhibits a price elasticity between -0.66 and -0.88, which is greatly driven by liquidity constraints. The last issue is however aggravated by the fact that these contracts are offered to farmers before the sowing season, a time when they are financially constrained the most. Additionally, the effects of marketing efforts that go into promoting these products have been discussed by Stein (2011). There are both endogenous and exogenous factors, a couple of which discussed in the book by Mahul and Stutley (2010) are as follows:

Systemic Risk: This refers to the risk that an adversity affects a large number of economic units simultaneously. Weather related risks are characteristically systemic since weather adversities usually affect large spans of area at the same time. The systemic nature of weather risks can generate major losses in the portfolio of insurers and this seriously affects their financial solvency. This prompts the insurers to share more of their risk portfolio and hence premia with reinsurers thereby, constricting their cash-flow.

Problematic Post-disaster Assistance Programs: Governments often provide direct compensations to disaster struck areas. This poses a “Samaritan’s dilemma”, because such policies discourage financial instruments of risk management such as insurance. Insurances provide more efficient financial solutions for both high and low intensity losses and reduce the accumulation of losses from recurrent events.

Limited Access to International Reinsurance Markets: Access to the international reinsurance market is often limited in developing countries, especially for specialised lines of business such as weather derivatives. China and India aside, smaller countries with fewer business opportunities may have more difficulty attracting reinsurers (Mahul and Stutley, 2010). Reinsurers are interested in crop and livestock programs that are properly designed and generate sufficient business.

Limited Agricultural Risk Market Infrastructure: This supply side impediment refers to availability of quality and long term weather data. Without establishing a functional and dense network of weather stations, such data are also not to be expected any time soon. This affects the accuracy of weather as well as crop risk models. Additionally any research or product development is impeded and leads to problems such as basis risk.

Low Risk Awareness: Stakeholder consultations in India and Mongolia reveal that farmers and herders recall the occurrence of major past events but tend to underestimate their severity (Mahul and Stutley, 2010). This lack of awareness quite understandably has its toll on participation in weather derivatives. Stein (2011) discusses the importance of marketing efforts in promoting these products.

Lack of Insurance Culture: Missing financial education and lack of understanding of insurance as a whole is a prominent problem. Insurance is often perceived as an unviable investment, because premia are collected every year but indemnities are paid much less frequently. Giné et al. (2007) points this out as they find that weather derivatives pays out only 11% of the time in South India.

Regulatory Impediments: The regulatory frameworks for diffusion and adoption of weather derivatives tend to be underdeveloped, as discussed on page 2. This is both a supply as well as a demand side impediment. New and innovative insurance products such as weather derivatives require an enabling regulatory framework for better reach.

Low participation: All the aforementioned problems, contribute in varying levels to low participation, which leads to weather derivative being an unviable financial investment unable to sustain without external financial and technical support. While many have suggested different ways to mitigate this problem, this chapter focuses on boosting the motivation of insurance seekers. With respect to the three summands (to be discussed in the next section), one can define three goals so as to boost participation in weather derivatives in developing countries.

1.3 The research questions

The dissertation is a collection of three essays on three different facets of weather derivatives. The first one deals with **Basis Risk**, the second one discusses the financial sustainability and the third one delves into an obscure yet overt issue of **Inter-temporal Adverse Selection** in weather derivatives. Although different, they all contribute towards elucidating the anomalies of demand for weather derivatives in developing countries. The research question posed in this chapter is how to mitigate high basis risks, lack of subsidies and elude adverse selection in order to boost participation? This body of work contributes to a growing literature by adding a new dimension, which is characterised by the three intrinsic motivations of an insurance seeker.

The first motivation is that of risk avoidance, arising from the attitude of risk-aversion. The essay on basis risks, points out how correlation of loss and payouts used by insurers leads to systematic over-estimation of efficacy. This leads to weather derivatives with high basis risks being offered. As a result, risk-averse farmers abstain from insurance participation. This issue has been discussed with an example of a Typhoon based insurance being offered for rice farmers in the Philippines. The question is how low should the basis risk be and how could one possibly reach it?

The second and the third motivations together reflect the rent seeking attitude of an insurance seeker. The second motivation is resultant of the attitude of seeking subsidy. Farmers often purchase insurance if there is a subsidy to the extent that their expected payout is greater than the subsidised premium. Weather derivatives are often offered without subsidy, moreover since the insurance seeker has to pay the insurer for underwriting the risk, the motivation resultant of the subsidy seeking attitude remains low. A possible solution has been offered in the third chapter through discussion of two cases in Nicaragua and Malawi. The question is how to restructure the products to simulate a **Phantom Subsidy**[3] to boost participation?

The third motivation is that of seeking the possibility to select adversely. Although actuaries try to minimise it, farmers take interest in weather insurance if they feel that they have better knowledge of the weather pattern than the insurer. As long as her expected payout is greater than the premium, her risk-averse instinct will be further encouraged to participate. However, this is not a permissible actuarial practice. The third essay discusses how in regions affected by major phenomenon, there is possibility that farmers can predict weather outcomes, which the insurers might overlook. The question is how to protect the insurer from adverse selection without discouraging the farmer from

[3]The term “Phantom Subsidy” has been used since it is not an actual subsidy but may be perceived as one.

participating?

1.4 A behavioural model

The motivation of this chapter is to present a model that draws a conclusion from the findings of the next three chapters. The second chapter comments on the high basis risk seen in weather derivatives, the third on the fact that weather derivatives are unattractive investment options and should be coupled with micro-finance, while the fourth comments on possibility of temporal adverse selection and ways to avoid it. A model roughly based on the one presented by Just et al. (1999) helps in reaching the motive. In their paper, Just et al. (1999) investigate adverse selection in case of multiple peril crop insurance offered by the United States Federal Crop Insurance Corporation (FCIC). Their model has been restructured to fit the framework of a weather derivative unlike the multiple peril crop insurance which they originally consider.

From Subsection 1.1.2, $\phi(y)$ and $p_y \cdot y$ are the revenues of a farm with and without weather derivatives. Assuming F and I as the subjective probability distribution of weather that Farmers and Insurers believe in respectively, one can surmise that insurance is sought if $\mathrm{P}[\phi(y) \mid F] \succ \mathrm{P}[p_y y \mid F]$. Assuming the preference function P(.) for an individual with von Neumann Morgenstern Utility function returns well-defined Certainty Equivalents (CE), it implies that: $CE[\phi(y) \mid F] - CE[p_y y \mid F]$ should be greater than zero. Taking cues from Just et al. (1999), but rearranging them to fit the given framework, this differential is decomposed into three summands:

$$CE[\phi(y) \mid F] - CE[p_y y \mid F] = \Delta_1 + \Delta_2 + \Delta_3 \tag{1.4.1}$$

where,

$$\Delta_1 = R[p_y y \mid F] - R[\phi(y) \mid F] \tag{1.4.2}$$

$$\Delta_2 = E[\phi(y) \mid I] - E[p_y y \mid I] \tag{1.4.3}$$

$$\Delta_3 = [E\{\phi(y) \mid F\} - E\{\phi(y) \mid I\}] - [E\{p_y y \mid F\} - E\{p_y y \mid I\}] \tag{1.4.4}$$

R being the risk premium, the first summand (Equation 1.4.2) refers to the motivation arising from an attitude of risk aversion. The second (Equation 1.4.3) refers to the motivation to enjoy subsidy and the third (Equation 1.4.4), is the motivation arising from an urge to select adversely against the insurer.

This chapter tries to elucidate the anomalies in insurance participation on the basis of the lessons from the three essays and how they affect the three aforementioned summands. However, while dealing with the first two summands, F and I are assumed to be same. It is only when the case of inter-temporal adverse selection is being discussed that their difference needs to be taken into consideration. This also goes by the *ceteris paribus* clause, whereby while considering basis risk or subsidies, one does not need to consider adverse selection at the same time.

1.4.1 The first summand

Going by the aforementioned argument, Δ_1 could therefore be rewritten as:

$$\Delta_1 = R\left[p_y y\right] - R[\phi(y)] \tag{1.4.5}$$

and it is the motivation to buy insurance (weather derivative in this case) due to risk aversion (Just et al., 1999). Equation 1.4.5, is merely the difference in risk premium of a farmer without and with weather derivatives hedging her portfolio. Here, R refers to the risk premium whereby, $R\left[py\right] \approx E\left[py\right] - CE[py]$ and $R[\phi(y)] \approx E[\phi(y)] - CE[\phi(y)]$.

The risk premium $[R(w)]$ can be approximated as:

$$R(w) \approx \frac{1}{2}\lambda\left[E(w)\right]\sigma_w^2 \tag{1.4.6}$$

from Arrow-Pratt measure of risk aversion where, $\lambda\left[E(w)\right]$ is the decision maker's absolute risk aversion at expected wealth $[E(w)]$. The absolute risk aversion is whereby defined as:

$$\lambda(w) = \frac{-u''(w)}{u'(w)} \tag{1.4.7}$$

where, $u'(w)$ and $u''(w)$ are the first and second derivatives of the utility function $u(w)$. Taking the power utility function where, $u(w) = \frac{w^{1\text{-}\theta}}{1-\theta}$, $\theta > 1$, the absolute risk aversion at w is:

$$\lambda(w) \quad = \quad \frac{\theta}{w} \qquad (from\, 1.4.7) \tag{1.4.8}$$

and therefore reflects Decreasing Absolute Risk Aversion (DARA), whereby the risk aversion of an individual decreases with increasing wealth $[w]$. The term $\frac{-u''(w)w}{u'(w)}$ represents a measure of relative risk aversion, and hence the power functions yields a case of Constant Relative Risk Aversion (CRRA), the degree of which is determined by the measure of risk aversion $[\theta]$ (Hardaker et al., 1997). Hence assuming DARA, $R(w)$ takes the form:

$$R(w) \approx \frac{\theta\sigma_w^2}{2E(w)} \qquad (from\, 1.4.6\, and\, 1.4.8) \tag{1.4.9}$$

As seen in Equation 1.4.9, in order to derive Equation 1.4.5, one needs to figure out the expected value and the variance of the revenue of the farm with and without weather derivatives. The expectation and variance of the revenue function with weather derivative is given by:

$$\begin{aligned} E\left[\phi(y)\right] &= E\left[p_y\left(\hat{y}_{max} + e_B\right) - \Gamma\right] \qquad (from\, 1.1.6) \\ &= p_y \cdot \hat{y}_{max} - \Gamma \qquad (\because E(e_B) = 0) \end{aligned} \tag{1.4.10}$$

$$and \qquad \sigma^2_{\phi(y)} = p_y^2 \sigma^2_{e_B} \qquad (\because\, p_y,\, \hat{y}_{max}\, and\, \Gamma\, are\, constant) \tag{1.4.11}$$

and those without weather derivative are given by:

$$E(p_y y) = p_y E(y) \qquad (from\, 1.1.6) \tag{1.4.12}$$

$$and \qquad \sigma^2_{p_y y} = p_y^2 \sigma_y^2 \qquad (from\, 1.1.6) \tag{1.4.13}$$

Therefore,

$$R[\phi(y)] \approx \frac{1}{2}\theta \left[\frac{p_y^2 \sigma_{e_B}^2}{p_y \cdot \hat{y}_{max} - \Gamma} \right] \qquad (from\, 1.4.9, 1.4.10\, and\, 1.4.11) \tag{1.4.14}$$

$$R[p_y y] \approx \frac{1}{2}\theta \left[\frac{p_y^2 \sigma_y^2}{p_y E(y)} \right] \qquad (from\, 1.4.9, 1.4.12\, and\, 1.4.13) \tag{1.4.15}$$

From Equation 1.4.5 one may derive:

$$\begin{aligned} \Delta_1 &= \frac{1}{2}\theta \left[\frac{p_y^2 \sigma_y^2}{p_y E(y)} - \frac{p_y^2 \sigma_{e_B}^2}{p_y \cdot \hat{y}_{max} - \Gamma} \right] \qquad (from\, 1.4.5, 1.4.14\, and\, 1.4.15) \\ &= \frac{1}{2}\theta \left[\frac{p_y \sigma_y^2 (p_y \cdot \hat{y}_{max} - \Gamma) - p_y^2 \sigma_{e_B}^2 E(y)}{E(y)(p_y \cdot \hat{y}_{max} - \Gamma)} \right] \end{aligned} \tag{1.4.16}$$

On the basis of the second chapter as well as the findings of Clarke (2011), it is known that weather derivatives are characterised by high basis risk. Basis risk is the standard deviation of the basis which in turn is the difference between the payout and the actual loss. In the model presented previously, e_B is the basis and therefore, σ_{e_B} is the basis risk (refer to Section 2.2). From this, taking partial derivatives, one may derive:

$$\frac{\partial \Delta_1}{\partial \sigma_{e_B}} = -\frac{\theta p_y^2 \sigma_{e_B}}{p_y \cdot \hat{y}_{max} - \Gamma} \qquad (from\, 1.4.16) \tag{1.4.17}$$

Equation 1.4.17 shows that under aforementioned conditions, the motivation of a risk-averse individual to seek insurance decreases with increasing basis risk of the weather derivative as well as the increasing measure of risk aversion of the decision maker. Assuming the premium is not higher than the expected maximum market return $[p_y \cdot \hat{y}_{max}]$, one may derive from Equation 1.4.16 that Δ_1 remains positive as long as:

$$\sigma_{e_B}^2 \leqslant \frac{\sigma_y^2 (p_y \cdot \hat{y}_{max} - \Gamma)}{p_y E(y)} \qquad (from\, 1.4.16) \tag{1.4.18}$$

From Equation 1.4.18, one sees that if a weather derivative is offered at fair premium, the difference of expected maximum market return $[p_y \cdot \hat{y}_{max}]$ and the fair premium $[\Gamma]$ is equal to the expected market return $[p_y E(y)]$. Consequently, it remains attractive to a DARA insurance seeker as long as the basis risk is less than the production risk $[\sigma_{e_B} \leqslant \sigma_y]$, simply because it reduces the variance of her revenue. In real case, weather derivatives are offered at prices much higher than fair premium (see Sections 3.2.1 and 3.2.2) in addition, basis risks are high (see Table 2.3.3). This brings up the value of Γ as well as $\sigma_{e_B}^2$. Under such circumstances it is imperative that demand for such products remain low. The aim therefore is not only to hold the basis risk lower than the production risk but low enough to offset the additional loading factors.

1.4.2 The second summand

According to Just et al. (1999), Δ_2 is the motivation to cash on Subsidies. Going by the *ceteris paribus* clause and assuming F and I to be one and same, actuarially,

$$\Delta_2 = E[\phi(y)] - E[py] \tag{1.4.19}$$

This is simply what the insurer thinks is the difference between the expected revenues with and without insurance. In case the premium is heavily subsidised, Δ_2 and with it the motivation enhances. However, since most weather derivatives are private, Δ_2 is negative to compensate the underwriter for carrying risk. This does not bear well on the insurance seekers motivation. It is imperative that Δ_2 will be negative, but if one succeeds in bringing up its value, it will be possible to hold the sum shown in Equation 1.4.1 above zero.

So is there a way out? One has to look at this problem from a different angle altogether. Since subsidising a privately offered product is a matter of Government Policy, one should try to look at possible restructuring of the derivatives to simulate subsidy through price discounts. Price discounts are perceived very differently, as seen in marketing literature. For example, Grewal et al. (1998) find that purchase decision of consumers who do not have prior knowledge of a product is positively influenced by price discounts. Since the farmers in question fall under the same category, they may be assumed to behave similarly. The premium charged for a weather derivative comprises of the product of the fair premium and loading factor(s). Since fair premium is merely the expected payout, a loading factor which is greater than one, accounts for the overhead costs that are incurred in the process of underwriting the risk. It mainly comprises of administrative costs, marketing and acquisition costs, loss adjustment costs, reinsurance costs, as well as profit and reserve[4]. Assuming weather derivatives are not subsidised, one needs to consider ways of decreasing the loading factors.

Major weather derivative providers like BASIX (India), BAAC (Thailand) or Opportunity International, are also involved in micro finance. When crop loans are offered[5], the high rate of interest (around 24% p.a.) is justified mainly on grounds of risk of loan default the Micro Finance Institu-

[4] For a detailed discussion please refer to Smith and Watts (2009).

[5] Based on personal experience in appraisal, disbursement and recovery of micro-credit while working in BASIX from 2002 through 2006.

tion (MFI) underwrites[6] in lieu of the actual creditor (which usually are commercial banks). One of the risks of loan loss covered by the interest rate is weather risk[7]. However, when these MFI sell a weather derivative to the same farmer, she gets double insurance for the same risk. Theoretically or morally there is no problem with this construct. In case of an adverse weather event, a farmer gets her credit waived and also gets a payout to smoothen her consumption. However, the MFI encourage the lenders to repay the loans from the payouts to avoid a lower credit rating in the next season, when they seek another loan. It is not easy for the MFI to do otherwise, because despite insurance coverage, farmers not paying back simply brings up the default rate of the MFI and affects its market competitiveness and its ability to raise funds from donors and commercial banks alike. The farmers' reaction to this construct is reported by Giné and Yang (2009) where they show through a randomised field experiment in Malawi that farmers prefer credit without insurance cover when there is implicit insurance in the credit contract due to a limited liability clause, as is the case of most micro-credits. A detailed discussion is beyond the scope of this work. The crux however is that there is scope of restructuring the loading factors to boost participation.

The argument of restructuring the products and the need thereof is cemented by the findings of the third chapter. In this chapter entitled: "Paying for the Pay-off Period", an analysis of the pay-off periods of two weather derivatives in Nicaragua and Malawi show that as an investment option, weather derivatives are not very lucrative for an insurer. However, it is a necessary proxy to crop insurance. Therefore, it is important to find ways to make it financially sustainable. It is being proposed to couple it with existing micro-credit, the demand for which is high among resource constrained agrarian societies. In conjunction to increasing participation, if properly priced, this compound product could also bring up the value of Δ_2 and thereby enhance the motivation to buy weather derivatives.

Given the cost or rate of interest of crop loans $Z = z + \gamma_f T_{MFI}$, where Z comprises of the

[6] Four major factors behind these rates are (i) the cost of capital; (ii) the MFI's operating expenses; (iii) loan losses; and (iv) generate reserves to expand their capital base and fund future growth. For more details please refer to Fernando (2006).

[7] BASIX in addition to selling its lenders weather derivatives, also bought the same to insure its portfolio (Skees and Barnett, 2006), the cost of which was borne by the lenders through the interests they paid.

premium paid by the MFI to insure against weather risk $\left[\gamma_f T_{MFI}\right]$, and other costs $[z]$, which include the cost of capital and that of underwriting default risks arising from sources other than weather. The premium $\gamma_f T_{MFI}$, is depicted here as the product of the fair premium γ_f and T_{MFI}, which is the loading factors a MFI pays to the insurer. The insurance seeking farmer's premium $\Gamma = \gamma_f T_F$, where T_F is the loading factor for an individual farmer when she buys a weather derivative as a stand alone product[8]. Hence, for a farmer seeking micro-credit and weather insurance as two stand alone products (characterised by subscript S) for the same portfolio, the cost is:

$$Z + \Gamma = z + \gamma_f \left(T_{MFI} + T_F\right)$$

Therefore the premium $[\Gamma_S]$ she pays to insure against weather related risks is:

$$\Gamma_S = \gamma_f \left(T_{MFI} + T_F\right) \tag{1.4.20}$$

due to the aforementioned double insurance for same risk portfolio.

In case of a coupled product (characterised by subscript C), where micro-credit and weather derivative is sold as a package and not two individual products, the cost could be $Z_C = z + \gamma_f T_C$ where, T_C is the loading factor for the weather insurance head of Z_C, such that: $(T_F + T_{MFI}) \geqslant T_C \geqslant T_{MFI}$. As long as $T_C < (T_F + T_{MFI})$, the farmer might experience a Phantom Subsidy $[S_C]$, given the other option is to incur a cost of $Z + \Gamma$. This is because of her cost savings which amounts to:

$$\begin{aligned} S_C &= Z + \Gamma - Z_C \\ &= \gamma_f \left(T_{MFI} + T_F - T_C\right) \end{aligned} \tag{1.4.21}$$

Whereby, her "phantom subsidised" premium of the coupled product $[\Gamma_C]$ is:

[8]The loading factor an insurer charges a MFI is assumed to be lower than that for an individual farmer simply because of the difference in the volume of the portfolio.

$$
\begin{aligned}
\Gamma_C &= \Gamma_S - S_C && (1.4.22)\\
&= \gamma_f(T_{MFI} + T_F)\\
&\quad -\gamma_f(T_{MFI} + T_F - T_C) \qquad (from\, 1.4.20\, and\, 1.4.21)\\
&= \gamma_f(T_C) && (1.4.23)
\end{aligned}
$$

Under this construct that she purchases the coupled product (micro-credit and weather derivative), her new revenue $[\phi_C(y)]$ with weather derivative may be rewritten as:

$$
\begin{aligned}
\phi_C(y) &= p_y[\hat{y}_{max} + e_B] - \Gamma_C \qquad (from\, 1.1.6)\\
&= p_y[\hat{y}_{max} + e_B] - \gamma_f(T_C) \qquad (from\, 1.4.23)
\end{aligned}
$$

In comparison, if she purchases micro-credit and weather derivative as individual products, her revenue $[\phi_S(y)]$ is:

$$
\begin{aligned}
\phi_S(y) &= p_y[\hat{y}_{max} + e_B] - \Gamma_S \qquad (from\, 1.1.6)\\
&= p_y[\hat{y}_{max} + e_B] - \gamma_f(T_F + T_{MFI}) \qquad (from\, 1.4.20)
\end{aligned}
$$

So a comparison of the value of the second summand, with and without the coupled product, represented by Δ_2^C and Δ_2^S respectively is given by:

$$\begin{aligned}
\Delta_2^C - \Delta_2^S &= E\{\phi_C(y)\} - E(py) - [E\{\phi_S(y)\} - E(py)] \qquad (from\, 1.4.19) \\
&= E\{\phi_C(y)\} - E\{\phi_S(y)\} \\
&= [p_y \hat{y}_{max} - \Gamma_C] - [p_y \hat{y}_{max} - \Gamma_S] \qquad (from\, 1.4.10) \\
&= \gamma_f(T_F + T_{MFI}) - \gamma_f(T_C) \qquad (from\, 1.4.20\, and\, 1.4.23) \\
&= \gamma_f(T_F + T_{MFI} - T_C)
\end{aligned}$$

As the market matures and the conditions get fairer for the farmer, the loading factor $[T_C]$ of the coupled product tends towards that which the MFI pays $[T_{MFI}]$. Therefore, at the limits $\Delta_2^C - \Delta_2^S$ is:

$$\lim_{T_C \to T_{MFI}} \gamma_f(T_F + T_{MFI} - T_C) = \gamma_f(T_F)$$

which means that at the limits,

$$\lim_{T_C \to T_{MFI}} \Delta_2^C = \Delta_2^S + \gamma_f(T_F)$$

Since, $\left[\gamma_f(T_F)\right]$ is always positive, one can argue:

(1.4.24)
$$\lim_{T_C \to T_{MFI}} \Delta_2^C > \Delta_2^S$$

This shows that coupling micro-credit with weather derivatives and pricing it accordingly (in comparison to offering it as a stand alone product), will contribute towards improving participation as it increases value of Δ_2. This effect may be attributed to the fact that the farmer, through price discount, enjoys a Phantom Subsidy of the order of S_C. It should be emphasised that this is referring to only those farmers who are looking for credit and insurance. For ones who look for one product or the other, the product should also be offered separately. Although in the case where the farmer is herself looking for insurance, the question of demand anomaly does not come to play.

1.4.3 The third summand

Δ_3 mirrors the motivation arising from the fact that the farmer thinks she has better information on the outcome than the insurer (Just et al., 1999), in other words it is motivation one derives from the opportunity of adverse selection. The third summand is:

$$\Delta_3 = [E\{\phi(y) \mid F\} - E\{\phi(y) \mid I\}] - \left[E\left\{p_y y \mid F\right\} - E\left\{p_y y \mid I\right\}\right] \qquad (from\, 1.4.4)$$

From the fourth chapter, one sees that there is a possibility of inter-temporal adverse selection resulting from information asymmetry due to the farmer reading a weather related clue better than the insurer. The chapter also presents a way to estimate the financial implication of this information asymmetry. Given, the insurer perceives that there is a significant effect to be expected, she should find ways to elude it without turning the third summand negative and deterring the insurance seeker. The motivation is positive when $\Delta_3 > 0$, but this amounts to promoting adverse selection and is not actuarially advisable even as a marketing tool. However, one may ponder the possibility of making $\Delta_3 = 0$, so that neither is the insurers' balance sheet exposed nor is the insurance seeker deterred.

Adverse selection may be classified as spatial and inter-temporal. Luo et al. (1994) explains "spatial adverse selection", as a phenomenon caused by using a geographic area as a risk-pooling group for crop insurance. For example, Just et al. (1999) demonstrate that for farmers with no historical yield data, premium calculation of the Multiple Peril Crop Insurance (MPCI) is based on the average yield over a county in the United States. As a result, farmers with a higher-than-county-average loss risk purchase insurance, while those with lower-than-county-average loss risk do not participate.

Luo et al. (1994, p: 441) in their paper explain, "lntertemporal adverse selection refers to the behaviour of an insurance buyer selecting only high-risk periods to purchase insurance with no adjustments being made by the seller to reflect this behavioural pattern". In case of weather derivatives this problem is often overlooked, since weather in a locality affects everyone the same way, as long as the meteorological station is local. Literature mostly report weather derivatives to be free of adverse selection (Alderman et al., 2007; Mahul, 2009; Skees, 2001), but this is true in case of "spatial adverse selection". This might be entirely true for most locations not affected by major weather phenomenon (like the El Niño, the La Niña or the India Ocean Dipole), where the possibility of "inter-temporal adverse selection" is not present. As one might guess, inter-temporal adverse selection arises from information asymmetry arising at one point of time due to information received at an earlier point of time. However, in places affected by such major weather events, where certain weather patterns linger for months, inter-temporal adverse selection is a risk worth considering.

As a solution, Luo et al. (1994) recommend differential pricing although, they along with Skees and Reed (1986); Goodwin (1993); Miranda (1991) agree that over time this leads to higher premia and a more adversely selected market in case of MPCI. In case of weather derivatives, similar outcomes may be expected. Differential pricing might make weather derivatives too costly for cash constrained farmers in bad years and in good years it gives unnecessary signals of a favourable harvest, leading to dwindling demand. Therefore, the way out is to make the farmers enter into contract before the weather related clue presents itself. A detailed description of the methodology to indentify the critical point of time has been presented in Chapter Four.

Equation 1.4.4 is the incentive that an insurance seeker derives from the opportunity of adverse selection. It is clear that once the two distributions F and I are same, so that there is no information asymmetry any more, the summand Δ_3 becomes zero and there is no possibility of adverse selection any more. In the case of inter-temporal adverse selection, this translates to finding a point in time when the farmer receives a weather related clue, cause before that, F and I are same and there is no information asymmetry. This does not provide the farmer any extra motivation but at least does not deter her from participating. However, rescheduling a contract to the optimal point of time serves three distinctive benefits:

1. Differential pricing is arguably a suboptimal strategy, selling weather derivatives before the critical time enables the insurer mitigate the financial repercussions of adverse selection

without leading to adversely selected markets.

2. On proper timing, one should take into consideration that it is an important factor in boosting participation. Although it is beyond the scope of this research, it is a well known fact that farmers are most liquid after harvest and most cash strapped before sowing. If the crop insurance for the subsequent season is offered right after the harvest in the preceding season, the effect of the financial constraint behind low participation (Cole et al., 2013) could be reduced to some extent. Further research in this regard is recommended.

3. Since the derivative is sold at an earlier date, the premium can be discounted, which in turn will contribute towards Δ_2. The premium being Γ, if the derivative is sold t periods of time before the season which it covers, the discounted premium Γ_D is given by:

$$\begin{aligned} \Gamma_D &= \Gamma e^{-rt} \\ \therefore \quad \Gamma_D &< \Gamma \end{aligned} \tag{1.4.25}$$

where, r is the rate of return the insurer gets from other investments. It has been proved earlier that subsidies or discounts lead towards a better Δ_2 and hence higher motivation to participate. As seen in the Subsection 1.4.2, premia Γ_C being lesser than Γ_S (as can be derived from Equation 1.4.22) led to a higher motivation reflected by Equation 1.4.24. Similarly, this discounting of premium as seen in Equation 1.4.25, will lead to $\Delta_2^D > \Delta_2$ and hence a comparatively higher motivation to participate.

1.5 The Solutions

Weather derivatives are being promoted as a tool for mitigation of agricultural risks in developing countries. In comparison to conventional crop insurance products, it has pronounced advantages. It has lower moral hazard and spatial adverse selection problems. It is also cost effective to deliver, since the running costs are low because loss assessment is not required. The losses can be calculated and indemnities disbursed comparatively faster due its design features. The participation in these programmes can be boosted if one can keep the sum of the motivations $[\Delta_1 + \Delta_2 + \Delta_3]$ positive, by pursuing the following goals:

Goal 1: Keep the Δ_1 positive by bringing down the basis risk. As discussed further in the second chapter, if one designs a weather derivative with respect to a particular weather variable (temperature, precipitation or wind speed), she needs to check if the variable affects the yield at all. Case studies from Philippines discussed hereafter, show wind indexed derivatives which do not mirror the actual losses of rice yield, have high basis risks. Although it is difficult to get rid of basis risks, keeping it lower than the standard deviation of the yield of the crop and lower enough to offset the loading factors, will improve Δ_1 and hence participation. Equation 1.4.18 and the discussion presented thereafter provides a guideline for insurers to determine the critical level.

Goal 2: Δ_2 is and will remain negative, since the insurance seeker has to pay for underwriting the risk. If there is no subsidy, the goal is to raise Δ_2 to a comparatively higher value by restructuring the product. Chapter Three comments on how weather derivatives are financially unattractive to insurers due to high initial costs and low sales volumes, among other factors resulting in prolonged pay-off periods. Integrating it with micro-credits, which have characteristically high demand, will boost its demand and shorten the pay-off periods considerably. Moreover, if the coupled products are properly priced, in line with the lessons of Subsection 1.4.2, the motivation will get an additional boost.

Goal 3: If there is a possibility of adverse selection, try to hold the Δ_3 at zero, by rescheduling the contract date. Inter-temporal adverse selection might happen in regions affected by major climatic events, where weather patterns persist for extended periods of time. Local farmers may base their insurance purchase decisions on the weather clue presented months in advance. This is detrimental for the insurers' reserve. It is not actuarially sound to allow adverse selection just to keep Δ_3 positive and differential pricing leads to an adversely selected market. Selling weather derivatives before the clue appears will maintain Δ_3 at zero, prevent skewing of market, mitigate financial repercussions and enable discounting of premia.

Weather derivatives, in its present form are hardly efficient tools of agricultural risk management. However, it fares better than traditional crop insurances in matters of moral hazard, adverse selection, cost of operation and timeliness of indemnification and hence serves as a necessary proxy. An effort to revamp its design to improve its demand is therefore logical. Keeping the farmers motivations in mind and restructuring them in a way so as to boost them will improve participation. **Bringing down Basis Risks still remain the pivotal issue in improving the effectiveness of weather derivatives as tools for mitigating agricultural risks in developing countries.**

Chapter 2

The Basics of Basis Risk

Abstract:

Typhoons perpetrate crop losses. 220 Typhoons were incident on the Philippines between 1970 and 2009. To hedge rice yield losses against high winds, two comparable insurance products have been implemented. Theory requires negative linear correlation between wind speed and rice yield for such products to be efficient, the products also assume this basic relation. This paper estimates their basis risks from the correlation between payouts and actual losses. Basis risks are found to be around 99%. To explain this anomaly, rice yields are regressed with pertinent Typhoon wind speeds, and other variables. Results of the regression explain the high basis risks. A thorough putative assessment of basis risk is necessary before implementing weather derivatives as a tool for poverty alleviation.

Keywords: basis risk; index based insurance; Typhoon insurance; weather derivatives

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This research was funded by the Deutscher Akademischer Austauschdienst (DAAD) and the data was collected during my research stay at the International Rice Research Institute, Los Banos, Philippines. A variant of this paper entitled: “Efficiency of Wind Indexed Typhoon Insurance for Rice” was presented at the 13th EAAE Congress, August 30- September 2, 2011, Zürich, Switzerland. A paper of the same title is under review for publication at an International Journal for Development Economics.

2.1 Introduction

Agriculture is highly affected by vagaries of weather. This has grave implications in developing countries where lack of safety nets render poor farmers vulnerable to vicious circle of poverty (Alderman, 2008). One of the major crops grown in developing countries is rice. 90% is thereby produced in Asia (IRRI, 2002). Rice fields cover 11% of the Earth's entire arable land, or more than 500 million hectares, making it one of the largest use of land for producing food and one of the most important economic activities on earth (IRRI, 2010). Additionally, rice consumers and growers form the bulk of the world's poor and it is grown on more than 250 million Asian farms, mostly smaller than one hectare. It is eaten by nearly half the world's population and it is the single largest food source for the poor (IRRI, 2010). Some of the major rice growing areas of the world, namely in Southeast Asia and on the Indian sub-continent, are exposed to weather extremes like cyclones which are expected to grow more frequent and stronger due to Global Climate Change (Solomon et al., 2007). The Philippines is a major producer and importer of rice which is also a staple diet for the people who are mostly poor. The analysis of satellite data showed 220 Typhoons of various intensities were incident on the archipelago in the last forty years. In order to hedge rice yield losses against high winds caused by Typhoons, they have two comparable insurance products, one from the Philippine Crop Insurance Corporation (PCIC) and another from MicroEnsure, which are both structured as weather derivatives.

Operation costs are low in case of weather derivatives and payouts are determined faster as compared to conventional crop insurances, since there is no need for loss assessment (Skees et al., 2007). Since the payout is derived on the basis of weather outcomes and not yield, a farmer cannot tamper with the outcome which is usually causes the problem of moral hazard in case of traditional insurances. Moreover, since weather is same for all in a region served by a single weather station, farmers do not have significant differences in weather risk, this also solves the problem of adverse selection, whereby risk prone individuals avail insurances and the ones with less risk find it uneconomical (Doherty, 2000). Although these have served as strong arguments in favour, basis risk, which is an inherent problem of all insurance products greatly affects weather derivatives (Woodard and Garcia, 2008) thereby, inversely affecting their efficacy as hedging instruments. *Basis* is the value differential between a call and put option. In the case of weather derivatives, this is the difference between loss and payouts. *Basis risk*, therefore, is the risk of a position in a hedging strategy, caused by the imperfect correlation between loss and payouts. For the insurer, this can lead to payouts higher than necessary, but more than that, it also affects the demand. In developing countries, where one is primarily dealing with illiterate farmers, high basis risk sends confusing messages as farmers often decide to purchase insurance based on their previous experience regarding payouts (Garrido and Zilberman, 2008).

This chapter intends to identify the underlying basis risk in weather derivatives exemplified with the two insurance products in Philippines. The chapter comprises of two parts, the first estimates the extent of basis risk, entailed by the two products. The second part elucidates the reasons why basis risk appears in these cases. Section 2.2, discusses the theoretical background of basis risk. This is followed by a brief discussion of the aforementioned insurance products. Next, the basis risks of these insurance products are estimated. Section 2.4 then deals with the reason behind basis risk in these cases, whereby the relation between wind speed and rice yield is put to test. This is done by studying the effect of Typhoons on rice crops through a series of regressions. The final section presents a conclusion and discusses further research opportunities.

2.2 Basis risk

Weather derivatives have been discussed at length in Subsection: 1.1.2 on page 3. From the stylised construct one gets an introduction to the concept of Basis risk. Basis risk results from an imperfect correlation between loss and payouts and therefore has been cited as a primary concern for the implementation of weather hedges (Brockett et al., 2005; Deng et al., 2007; Turvey, 2001; Turvey et al., 2006). It is expressed as the standard deviation of optimal basis or the hedging error at optimal hedging ratio $\left[\sigma_{HE}^{a^\star}\right]$, which is the minimum variance hedging ratio for a risk-averse expected utility maximizing consumer in a Mean-Variance framework[1]. Assuming an insurance seeker is charged fair premium and there is no transaction cost, her hedging error $[HE]$ is defined as:

$$HE = X - aY \tag{2.2.1}$$

where, X is the loss (net of fair premium) calculated as the difference between observed seasonal yield and the average yield estimated from Typhoon free seasons. Y is the payout (net of fair premium), per unit insurance policy and a is the hedging ratio. Although it appears different, it is simply Equation 1.1.6 expressed in terms of losses, as a function of a, at fair premium, at absolute values (overlooking the price term). This restructuring brings down the data requirement significantly, which is welcome when one deals with developing countries. Therefore, the expected value of X and Y is:

$$E(X) = E(Y) = 0 \tag{2.2.2}$$

and have finite moments for the random variable X and Y. The basis risk may hence be defined as the Standard Deviation of the hedging error:

$$\sigma^a_{HE} = \sqrt{Var(X - aY)} \qquad (from 2.2.1)$$

Minimization of variance of HE expressed by $min_a[Var(X - aY)]$ yields the minimum variance hedging ratio $a^{\star}$, given by:

[1]Since in this case one is dealing with insurance products and since Philippines has no *Derivative Market* one does not need to adopt the methodology suggested in Woodard and Garcia (2008). Instead a method, whereby basis risk is estimated directly from coefficient of correlation, based on minimum variance hedging ratio for a risk-averse expected utility maximizing consumer should suffice.

$$\begin{aligned} min_a[Var(X-aY)] =& min_a[Var(X)-2aCov(XY)+a^2Var(Y)] \\ =& min_a[E(X^2)-E(X)^2-2aE(XY)-E(X)E(Y) \\ & +a^2E(Y^2)-E(Y)^2] \\ =& min_a[E(X^2)-2aE(XY)+a^2E(Y^2)] \qquad (from 2.2.2) \end{aligned}$$

Taking First Order Condition with respect to a equated to 0:

$$\begin{aligned} \frac{d\left[E(X^2)-2aE(XY)+a^2E(Y^2)\right]}{da} &= 0 \\ -2E(XY)+2aE(Y^2) &= 0 \end{aligned}$$

which gives the minimum variance hedging ratio $a^\star$ as:

$$a^\star = \frac{E(XY)}{E(Y^2)} \tag{2.2.3}$$

Since Pearson's Product Moment Correlation Coefficient of X and Y (ρ_{XY}) may be alternatively expressed as:

$$\begin{aligned} \rho_{XY} &= \frac{Cov(XY)}{\{Var(X)Var(Y)\}^{1/2}} \\ &= \frac{E(XY)-E(X)E(Y)}{\sigma_X\sigma_Y} \\ \text{or, } \rho_{XY} &= \frac{E(XY)}{\sigma_X\sigma_Y} \qquad (from 2.2.2) \\ \text{or, } E(XY) &= \rho_{XY}\sigma_X\sigma_Y \end{aligned} \tag{2.2.4}$$

$a^\star$ can be alternatively expressed as:

$$a^{\star} = \frac{E(XY)}{E(Y^2)} \qquad (from 2.2.3)$$
$$= \frac{\rho_{XY}\sigma_X\sigma_Y}{\sigma_Y^2} \qquad (from 2.2.4) \tag{2.2.5}$$
$$= \rho_{XY}\frac{\sigma_X}{\sigma_Y}$$

Substituting a by $a^{\star}$ gives basis risk as:

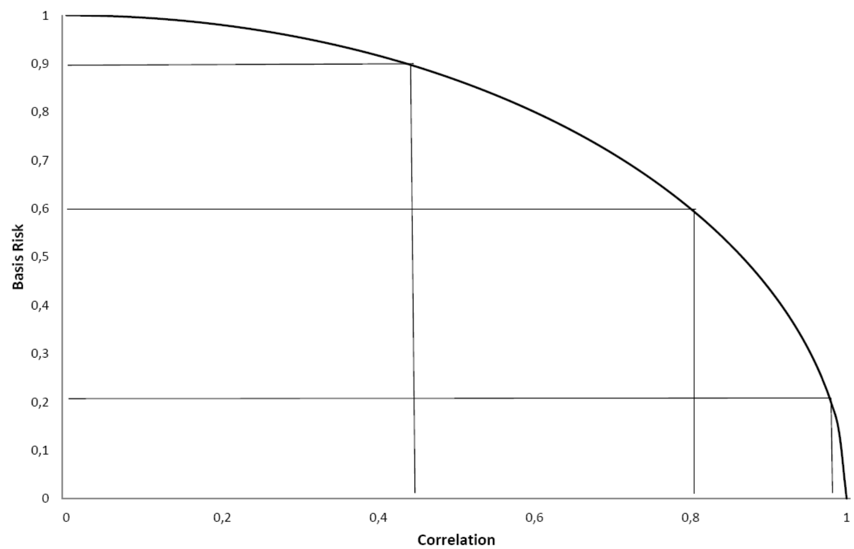
$$\sqrt{Var(X-a^{\star}Y)} = \sqrt{Var(X) - 2a^{\star}Cov(XY) + a^{\star 2}Var(Y)}$$
$$= \sqrt{\sigma_X^2 - 2\rho_{XY}\frac{\sigma_X}{\sigma_Y}\rho_{XY}\sigma_X\sigma_Y + \rho_{XY}^2\frac{\sigma_X^2}{\sigma_Y^2}\sigma_Y^2} = \sqrt{\sigma_X^2 - 2\rho_{XY}^2\sigma_Y^2 + \rho_{XY}^2\sigma_Y^2} \qquad (from 2.2.5)$$
$$= \sqrt{\sigma_X^2(1-\rho_{XY}^2)} = \sigma_X\sqrt{1-\rho_{XY}^2}$$

Standardizing this expression, the basis risk is estimated by:

$$\sigma_{HE}^{a^{\star}} = \sqrt{1-\rho_{XY}^2} \tag{2.2.6}$$

This means that basis risk denoted by the standard deviation of optimal basis or $\sigma_{HE}^{a^{\star}}$ can be estimated independent of the hedging ratio and net of actuarially fair premium. In Figure 2.2.1 Equation 2.2.6 is plotted, showing that the basis risk in an insurance product increases as the correlation between the pay-out and the actual loss decreases. The increase is steep as the correlation falls to 80%, whereby the basis risk already rises to 60%. Beyond this point the rise is gradual. Once the correlation falls to 45%, the basis risk is already as high as 90%.

Figure 2.2.1: Payout-Loss correlation and Basis Risk



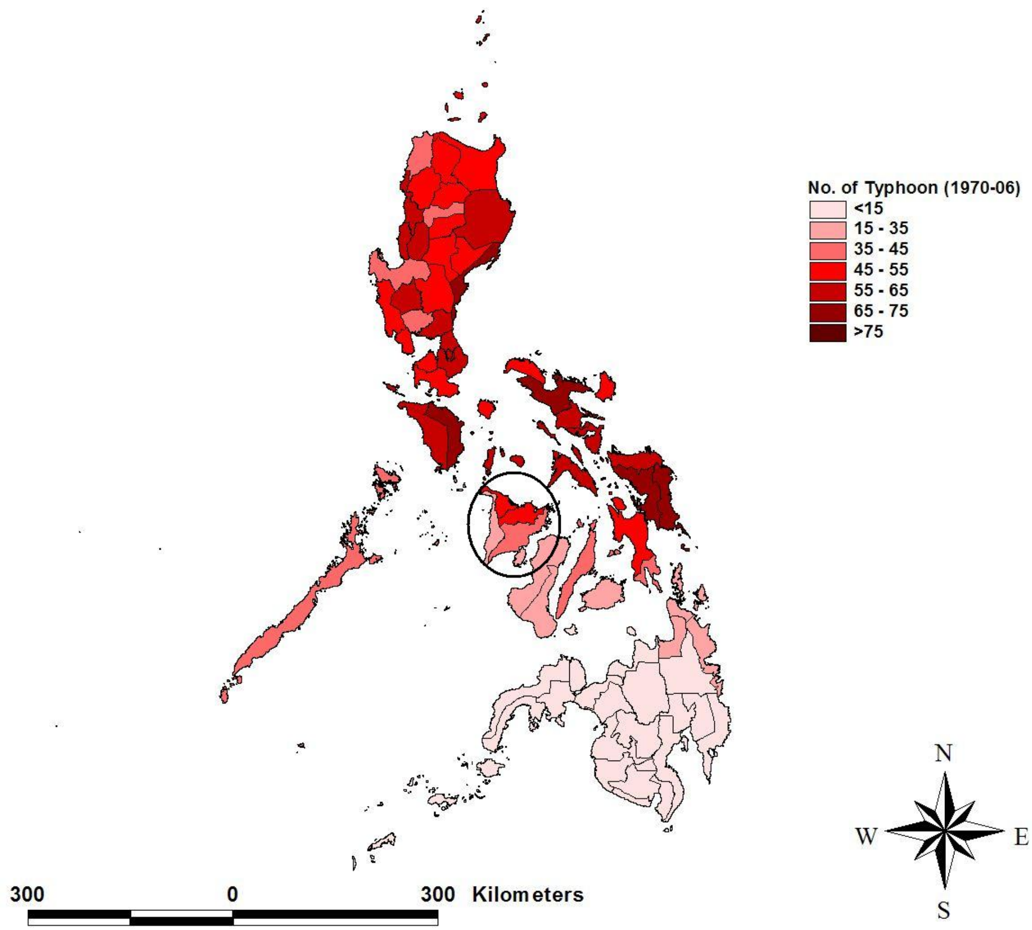
Source: Own analysis.

2.3 The Cases

Two organisations, namely The Philippine Crop Insurance Corporation (PCIC) and MicroEnsure [2] have launched insurance programs to hedge the effects of Typhoons on rice, with wind speed as the index correlated to yield loss. While PCIC has a nation wide insurance program, MicroEnsure provided it only for the Panay islands (encircled in Figure 2.3.1) in 2009 as a pilot. Panay comprises of five provinces namely Aklan, Antique, Capiz, Iloilo and Guimaras. Due to lack of yield data, Guimaras is excluded from the analyses. For the purpose of this study, only the aforementioned four provinces were considered as they allow a comparative study of the products of both the organisations.

[2]This paper has been written with their permission, on the basis of information provided by them and the author gratefully acknowledge their cooperation in this regard.

Figure 2.3.1: Map of Typhoon hotspots in the Philippines



Source: Own illustration based on satellite data on Typhoon tracks from JTWC (2006).

PCIC runs a nation-wide insurance program and has a diverse set of products[3]. The product being considered is the "Rice and Corn Crop Insurance", which insures against natural calamities (Typhoons, floods, drought, earthquakes and volcanic eruptions), plant diseases and pest infestation. From this portfolio, only the Typhoon related product was chosen since it is structured like a weather derivative. After the occurrence of a Typhoon, the period of time for which the field was exposed to the Typhoon (6, 12 or 24 hours) and the level of maturity of the standing crop (booting, flowering or mature) are taken from satellite data and rule of thumb respectively. Based on these

[3]The information provided is on the basis of discussions held with officials of the organisation on July, 2007.

two factors and the speed of wind, which is objectively measured by a meteorological station, the extent of loss is calculated according to a “Revised Claim Settlement Approach and Loss Prediction Table (RECSAP)” (seen in Table 2.3.1). For the purpose of comparative analysis the pay-offs with 6 hour exposure were simulated.

Table 2.3.1: Revised Claim Settlement Approach and Loss Prediction Table of PCIC

Growth stage	Period of exposure (hours)	Wind velocities (km/h)		
		70-100	101-150	¿150
		Estimated yield loss (%)		
Booting	6	¡10	10-15	15-25
	12	10-15	15-25	20-30
	24	15-20	20-30	25-35
Flowering	6	10-15	15-25	25-35
	12	15-25	25-30	30-40
	24	25-30	30-35	35-50
Maturity	6	¡10	10-15	15-20
	12	10-15	15-20	20-25
	24	15-20	20-25	25-30

Source: Carmen N. Hutaba, PCIC, personal communication, 2007.

MicroEnsure has a similar product and has carried out a pilot in the Panay islands. For pay-off calculation they use the following formula:

$$Payout = W \times D \times S$$

Based on Table 2.3.2, W is the payout factor corresponding to the incident wind speed, D is the payout factor corresponding to the distance parameter and S is the sum insured. Since in the data matrix used for analyses in this chapter has only those provinces which fall within 50 km radius (100km diameter) of the eye of the Typhoon (refer to A.1 for Typhoon sizes), the distance parameter has been overlooked since all the cases are expected to have 100% of the calculated pay-off.

Table 2.3.2: Payout matrix of MicroEnsure for Panay island

Tropical Cyclone Type	Maximum wind speed (km/h)	Damage description	Payout factor (W)
Tropical Depression	¡ 95	N/A	0
Tropical Storm	95 to 117	N/A	0
Category 1	118 to 152	Minimal	0.2
Category 2	153 to 177	Moderate	0.6
Category 3	178 to 209	Extensive	0.9
Category 4	210 to 250	Extreme	1
Category 5	¿ 250	Catastrophic	1

$$D = \begin{cases} 1 & Distance < 50km \\ \frac{\max(150 - Distance)}{Distance} & 50km < Distance < 150km \\ 0 & Distance > 150km \end{cases}$$

where, *Distance* refers to the distance of the farm from the eye of the Typhoon.

Source: James E. Sharpe, MicroEnsure, personal communication, 2009.

Theory demands that the weather variable, in this case wind speed, be negatively correlated to yield of the crop in question. As evident from the payout matrices (see Table 2.3.1 and 2.3.2), both the products assume linear negative relation between rice yields and wind speed. For basis risk estimation, the expected payout of the insurance products are calculated by burn analysis[4] and correlated with the actual losses, net of fair premium. Assuming the trend value is the sum assured for a particular season, the yield loss is the deviation of the observed yield from the trend. The correlation in case of both products are extremely low (near zero) and even positive for the province of Iloilo (Table 2.3.3). Translated in terms of basis risk (written in bold italics), none of the products seem to be feasible due to their magnitude (approximately 94-99%).

[4] According to Odening et al. (2007) this is a good estimation of the expected payout especially since in this case, long term wind data (36 years) was available.

Table 2.3.3: Correlation coefficients and basis risks

PROVINCES	PCIC		MicroEnsure	
	IRRIGATED	RAINFED	IRRIGATED	RAINFED
AKLAN	-0.0192	-0.0403	-0.0226	-0.0423
	0.9998	***0.9992***	***0.9997***	***0.9991***
ANTIQUE	-0.1102	0.1234	-0.1177	0.1216
	0.9939	***0.9924***	***0.9930***	***0.9926***
CAPIZ	-0.1080	-0.0412	-0.1049	-0.0407
	0.9941	***0.9992***	***0.9945***	***0.9992***
ILOILO	0.3313	0.1370	0.2361	0.1484
	0.9435	***0.9906***	***0.9717***	***0.9889***

Note: The numbers in bold italics represent the corresponding basis risk.
Source: Own analysis.

Against the background of the theoretical link between pay-out correlation and basis risk (see Figure 2.2.1) the results lead to the conclusion that the products no longer hedge rice yield losses due to Typhoons but function as derivatives based on wind speed completely uncorrelated to yield losses. Although they might minimise the variance in household income through diversification, they can no longer be termed insurance or risk management tools since the original purpose stands defeated.

2.4 Empirical analysis

One wonders if the reason behind the high basis risks could lie in the design of the products itself. The products, in line with the theory assume a linear negative relation between wind speed and rice yields. To analyse if the assumption is really plausible, linear regressions are undertaken using determinants used in both the products. The five crop stages (described on page 46) are taken as proxy for the height of the standing crop. The period of exposure is excluded since data were taken at 6 hour intervals[5]. Similarly, distance parameter seen in product of MicroEnsure is excluded due to aforementioned reasons. In addition to that a year variable is included to detrend the data and

[5]Interviews revealed that under real circumstances, there is no way to ascertain how long a Typhoon lingered on which field and hence they too use 6 hour exposure as a rule of thumb, besides the data is based on the satellite imagery of Typhoon tracks which is taken at 6 hour intervals.

a seasonal variable to elucidate the effect of wet and dry seasons on the yield of rice. The model estimated is as follows:

$$
\begin{aligned}
yield_{(yr,pr,s,sys)} = {} & \alpha_1 s_{(dry,sys)} + \alpha_2 s_{(wet,sys)} + \alpha_3 yr \\
& + \sum_{i=1}^{4} \alpha_{i+3} ws^{max}_{(yr,pr,s,cr_{st_i})} + \varepsilon_{(yr,pr,s,sys)}
\end{aligned}
$$

where,

sys : refers to the cropping system, in this case irrigated, rain-fed or aggregate yield.

s : refers to the season, in this case dry (Jan-June) or wet (Jul-Dec).

pr : refers to the provinces.

yr : refers to year in this case 1970 to 2005.

$yield_{(yr,pr,s,sys)}$: is the yield of rice in a particular system, in a season, of a province in a year.

$s_{(dry,sys)}$ *and* $s_{(wet,sys)}$: are two dummy variables for the season being dry or wet in a particular cropping system.

$ws^{max}_{(yr,pr,s,cr_{st_x})}$: is the maximum recorded wind speed at a particular crop stage of rice in a season of a year at a province.

ε : refers to white noise.

cr_{st_x} : refers to the crop stage which is an ordinal classification of the 110 days of the rice crop into four stages.

Since the damage caused to the crops is believed to be directly proportional to the height of the standing crop (which PCIC classifies into 3 growing stages in Table 2.3.1 on page 42) 5 growing stages of the crop are taken as a proxy for height as described in the following paragraph:

Crop stages

- "Stage 0": in this case refers to Typhoon free seasons for the province. This is not a stage of the crop but was used for data filtering alone, to make sure that the yields in Typhoon free seasons are not a part of the regression matrix.

- "Stage 1": refers to the seedling stage of the crop and also when there is no standing crop. This is more a stage of the field than the crop. The two different conditions are recorded in one, since it is believed that Typhoons have no effect on the yield when it strikes at the seedling stage[6].

- "Stage 2": refers to the vegetative stage of the crop. It is usually found between the 6th and the 10th week as well as between the 27th and 31st week of the year in the dry and wet season crop respectively. It is termed as booting stage in Table 2.3.1.

- "Stage 3": refers to the reproductive stage of the crop. It is usually found between the 10th and the 15th week as well as between the 31st and 36th week of the year in the dry and wet season crop respectively. It is termed as flowering stage in Table 2.3.1.

- "Stage 4": refers to the maturity stage of the crop, which marks its maturity and harvesting stage. It is usually found between the 15th and the 19th week as well as between the 36th and 40th week of the year in the dry and wet season crop respectively.

The model is estimated using Ordinary Least Square, NLS and ARMA method on EViews 7.0, with White Heteroskedasticity consistent Standard Errors and Covariance. The sample size is 72 for Aklan, Antique, Capiz and Iloilo (2 seasons for 36 years). Additionally, the Ramsey-RESET Test for functional forms was carried out, but owing to the insignificance of subsequent fitted terms the linear model was adopted, which seemed better owing to the low AIC and BIC values as compared

6

– Personal communication with Agronomists at International Rice Research Institute, Philippines, 2007.

to models with other functional forms. A more compelling argument for assuming a linear model was the fact that the analysed products, in line with the theory, assume linear relation.

Satellite data on Typhoon tracks obtainable from Joint Typhoon Warning Centre (JTWC, 2006) is used to compile database on Typhoons passing through the Philippine isles from 1970 to 2006. The GIS software Arc view 3.2a is used to record:

1. The provinces affected by a Typhoon. A "footprint zone" is superimposed along the Typhoon track, with a width of 100 km[7], to obtain a generalized area of potential Typhoon damage, so as to record the provinces with 100% indemnification (Table 2.3.2).

2. The time of incidence. The provincial rice yield data for the various cropping systems (Irrigated, Rain-fed and Aggregated yield across both systems) and season (Dry season: January – June and Wet season: July – December) from 1970 to 2005 are obtained from the Philippine Rice Statistics Handbook published by the Bureau of Agricultural Statistics. The time of incidence also gives the most probable stage of the crop, when the Typhoon blew over the field (as described on page 46).

3. Recorded wind speed. A Typhoon[8] feeds on an incessant supply of latent heat released from condensation in ascending moist air. The reliance on readily available moisture also explains why tropical cyclones can only survive over the warm oceans and invariably weaken once over land (Brand and Blelloch, 1973). This means the wind speed of a Typhoon in an archipelago like the Philippines waxes and wanes as it passes land and water bodies intermittently. Therefore, the highest recorded speed is taken, since that gives an idea of the maximum damage caused by the Typhoon on the standing crop.

[7]For details on Typhoon size see Appendix A.1.
[8]Details regarding the wind speed and classification of Typhoons is provided in Table A.1.2.

Table 2.4.1: Expected values of the coefficients

PROVINCES	CROPPING SYSTEM	$s_{(dry,sys)}$	$s_{(wet,sys)}$	yr	$ws^{max}_{(yr,pr,s,cr_{(st_1)})}$	$ws^{max}_{(yr,pr,s,cr_{(st_2)})}$	$ws^{max}_{(yr,pr,s,cr_{(st_3)})}$	$ws^{max}_{(yr,pr,s,cr_{(st_4)})}$
AKLAN	AGGREGATE	1.1276	1.241	0.0613	-0.0003	-0.0013	0.0004	-0.0012
	YIELD	***0.1011***	***0.0924***	***0.0037***	***0.0008***	***0.002***	***0.0021***	***0.001***
	RAINFED	0.977	1.0769	0.0395	-0.0008	-0.0006	0.0014	-0.0004
		0.0684	***0.0725***	***0.0029***	***0.0007***	***0.0023***	***0.0017***	***0.0012***
	IRRIGATED	1.5432	1.7136	0.0722	-0.0015	-0.0032	0.001	-0.001
		0.1452	***0.1403***	***0.0053***	***0.0012***	***0.0019***	***0.003***	***0.0015***
ANTIQUE	AGGREGATE	1.5232	1.511	0.0465	-0.0016	0.0043	-0.0022	0.0019
	YIELD	***0.0788***	***0.0955***	***0.0034***	***0.0013***	***0.0039***	***0.0013***	***0.002***
	RAINFED	1.2288	1.2213	0.0293	-0.0014	0.0023	-0.0001	0.0006
		0.0847	***0.0898***	***0.0035***	***0.001***	***0.0036***	***0.0023***	***0.0018***
	IRRIGATED	2.3428	2.3064	0.0343	-0.0029	0.0038	-0.0031	0.0052
		0.1283	***0.1251***	***0.0046***	***0.0018***	***0.005***	***0.0023***	***0.0033***
CAPIZ	AGGREGATE	1.551	2.0165	0.026	0.0006	-0.0005	0.0008	-0.0028
	YIELD	***0.1372***	***0.105***	***0.0042***	***0.0008***	***0.0024***	***0.0013***	***0.0014***
	RAINFED	1.5307	1.9789	0.021	0.0006	-0.0006	0.001	-0.0025
		0.1043	***0.1106***	***0.0044***	***0.001***	***0.0035***	***0.0027***	***0.0018***
	IRRIGATED	2.3157	2.9988	0.0194	-0.0004	0.0004	0.0002	-0.004
		0.1877	***0.1938***	***0.0067***	***0.0014***	***0.0029***	***0.0021***	***0.002***
ILOILO	AGGREGATE	1.466	1.7487	0.0405	0.0004	0	0.0013	0.0012
	YIELD	***0.0976***	***0.0982***	***0.0039***	***0.0008***	***0.0021***	***0.0033***	***0.0014***
	RAINFED	1.3051	1.5444	0.0302	0.0002	0.0021	0.0015	0.0008
		0.089	***0.0934***	***0.0038***	***0.0008***	***0.0033***	***0.0024***	***0.0014***
	IRRIGATED	2.2645	2.1801	0.0352	-0.0006	-0.0003	-0.0003	-0.0015
		0.0464	***0.0467***	***0.0017***	***0.0003***	***0.0007***	***0.0007***	***0.0006***

Note: The numbers in bold italics represent the respective standard errors.
Source: Own analysis.

2.5 Results

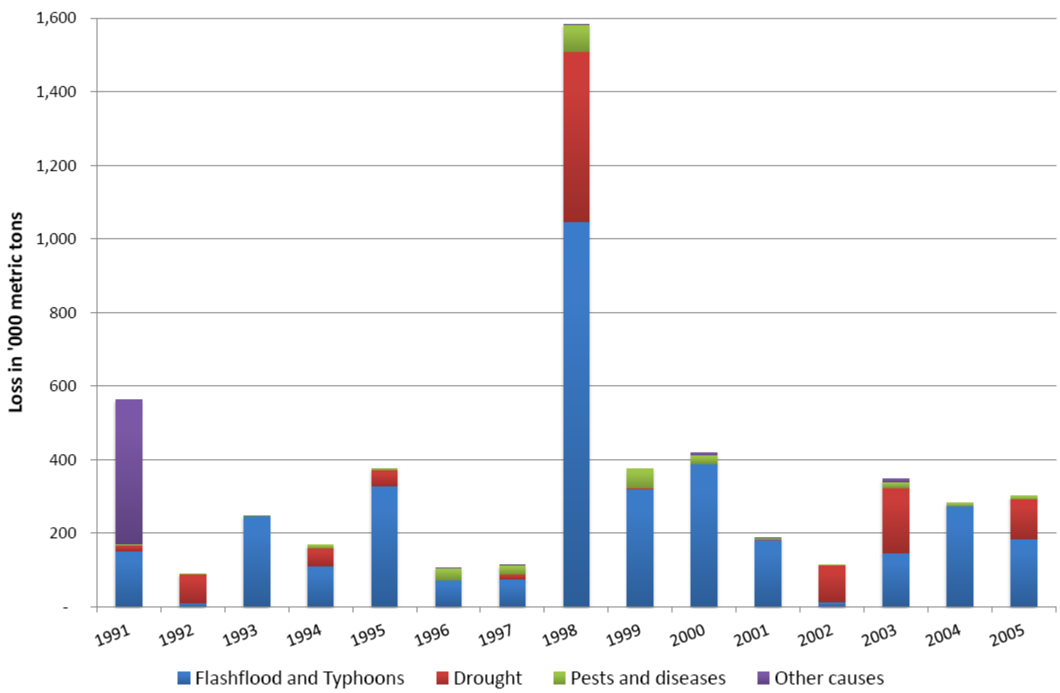
Rice yield at a national level across all cropping systems shows steady rise from 1970 through 2005 with occasional lows but without major structural breaks. Therefore, to avoid loss of information and preserve the variance, yield losses were not de-trended from the central tendency using tools like ARIMA models, robust double exponential smoothing, or spline regression as suggested by Skees et al. (1997).

As seen in Table 2.4.1, $s_{(dry,sys)}$ is the expected yield in dry season, and $s_{(wet,sys)}$ in the wet season in the respective cropping systems in 1969 expecting no Typhoon. Both variables are highly significant at 1 percent level, since they are merely the intercepts giving the respective yields in wet or dry season in a given province with a given cropping system. yr, which is also highly significant (at 1 percent level) is the expected rate at which yield has increased over the period of time, possibly due to technological advances. The other four variables (wind speed at particular crop stages of rice) are all highly insignificant, showing conclusively that there is no or very little effect of wind speed on rice yields - across systems and provinces. This indicates that the stage of the crop at which the Typhoon is incident is of no importance, and the same goes for the season when it occurs. As a result the null hypothesis that wind speeds are not negatively and linearly related to rice yields could not be rejected. This finding explains the lack of correlation between the payouts and the actual losses seen in Table 2.3.3, which in turn explains the high basis risks of both the products.

2.6 Conclusion

Flash-floods and Typhoons are major reasons for rice crop losses in the Philippines (Lansigan et al., 2000), which could also be attributed to droughts, pests and diseases (Figure 2.6.1). Whether it is the wind or the accompanying flash flood that causes it, is an important question to be investigated if one intends to find an insurance against this recurrent phenomenon. Since, historical data regarding flash-flood incidences are not available, one has to come up with innovative methods to estimate the extent of flash-flood. One possibility might be modelling the angular acceleration of Typhoon systems. Since dry air is heavier than moist air, Typhoons decelerate after precipitating heavily. This is one of the main reasons why they grow weak on land and gain strength on water bodies which supply them with heat and moisture (Brand and Blelloch, 1973; Gray, 1968). Modelling angular deceleration might give a picture of the extent of incident flash floods and hence serve as an index. Flood indexing therefore seems to be a possible option that can hedge rice against Typhoons with better efficacy.

Figure 2.6.1: Causes of rice yield losses in the Philippines



Source: As reported by Lansigan et al. (2000), based on the Philippine Rice Statistics Handbook (BAS, 2008).

An estimation of basis risk from the correlation coefficients between payouts and losses shows that the analysed products entail high basis risks. To clarify, a regression analysis was undertaken as a next step. The results indicate that rice yield is mainly influenced by the amount of seasonal rain and the increase of yield over time due to technological advances. On the other hand, the influence of wind on the different crop stages was not found to be significant. Therefore, weather derivatives based on such assumptions, fail to mitigate weather risks due to high basis risks. Although we observe that this might have to do with the low head weight of the crop. In case of crops like maize, vegetables or plantation crops like banana in Caribbean, high winds might directly affect yield and is hence worth researching.

Products with high basis risk baffle farmers regarding the very concept of insurance, since they do not know how much payout to expect in face of weather related losses and eventually lose faith in these new products. As a result, it gets extremely difficult to sell them in subsequent seasons (Clarke, 2011). This inference is reflected in the findings of Giné et al. (2008), where they find that risk-averse farmers in South India abstain from buying rainfall indexed weather derivatives. It is therefore important that a thorough putative assessment be done to check for the extent of basis risk, no matter which instrument is applied to hedge the effects of Typhoons or any other weather phenomenon.

There is a considerable market for micro-insurance in areas of health, property, disability insurance to name a few. From the works of Clarke (2011); Cole et al. (2013); Giné et al. (2008); Stein (2011), one could infer that marketing or even piloting a weather derivative with high basis risk might affect the demand for other forms of insurance as well. Weather derivatives have inherent advantages in comparison to conventional forms of crop insurance. The pivotal issue is to bring down the basis risk in order to enhance their efficacy as instruments of weather risk management in agriculture.

Chapter 3

Paying for the Pay-off Period

Abstract:

Weather derivatives in developing countries are often discontinued post-pilot. Why? When do they start yielding returns? How to re-insure them? These are case specific questions. In this paper, pay-off period of two weather derivatives from Nicaragua and Malawi are estimated for increasing, decreasing and cyclic demands and the effects of loss ratio, risk retention and commission percent on their pay-off periods have been discussed. Donors, policy makers and insurers may use this method to answer those questions. If donor assistance ends before demonstrating the viability of a weather derivative, an insurer might be discouraged to continue the programme. A possible solution is coupling weather derivatives with micro-credit and piggy-backing on their ever increasing demand to shorten the pay-off periods.

Keywords: Index based insurance; weather derivative; break-even; reinsurance; loss ratio

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3.1 Introduction

Weather derivatives have been promoted over the last decade by international development organisations both through public and private insurance providers in the developing world (Hess et al., 2005). It is an innovative product with the potential to mitigate financial repercussions of adverse weather events on agriculture. Agricultural insurance ease the difficult task of donors and governments of intervening and supporting agriculture affected by adverse weather events. Such interventions – which often involve government policies of agricultural credit bailouts – have been popular but painfully counterproductive. In most developing countries, there are inherent limits to promotion of agricultural insurance in the form of named or multi-peril insurances, because of:

(i) Difficulty in controlling moral hazard, under which the insured behaves more riskily because of insurance cover and thus increase the probability of adverse outcomes.

(ii) Lack of check against adverse selection, whereby individuals with higher than average risk seek insurance and those with lower than average risks find it uneconomical (Doherty, 2000).

(iii) Underdeveloped infrastructure, due to which monitoring small individual risks gets expensive. Added to the limits, many weather related shocks are covariate in nature. Therefore, it is hard for insurance providers to efficiently and timely assess damages when it hits over a large span of area.

A novel solution is hence weather derivative, an insurance indexed to an objective indicator of weather such as rainfall or temperature. Depending on the crop and availability of data, indices like cumulative rainfall in a particular crop phase or the number of days with temperatures below or above a cut-off is in common use. Since weather is not affected by individual behaviour, and there is no asymmetry of information regarding weather events, weather derivatives are resilient to both moral hazard and adverse selection. Furthermore, since payouts are determined on the basis of objectively observed weather data from independent meteorological stations, monitoring costs are also minimised (Barnett et al., 2008). Owing to these advantages, international development organisations have been piloting them, expecting that insurers would eventually scale up those pilots into larger operations thus transferring risks from the agricultural sector.

The durations of these pilots are usually 3 to 5 years (Hess and Syroka, 2005), after which the programme is expected to self-sustain and scale up. Unfortunately, weather derivatives come with their own set of problems such as:

(i) Initial cost of designing a weather derivative is high: it is a relatively new form of insurance and often the experts are not available locally. Network of weather stations are often sparse, requiring setting up of new ones (Skees, 2008).

(ii) Weather derivatives usually entail high basis risk (Woodard and Garcia, 2008), which is the lack of correlation between indemnification and actual loss (Banerjee and Berg, 2011). This often leads to risk-averse farmers not buying policies after inadequate indemnification (Hogarth and Kunreuther, 1989).

(iii) Weather derivatives are difficult to scale up, due to additional reasons as discussed by Giné et al. (2008); Skees (2008). High costs and low scale brings up the unit cost further.

(iv) Inherent systemic nature of losses in agriculture, make insurers retain less risk and transfer more of the business (risk and premium) to re-insurers who have large financial capacity.

As a result, returns to insurers come late. Despite the best of intentions, these programmes are often discontinued after the pilots end, as in cases of Ethiopia, Morocco, Ukraine, and parts of Mexico and India, among others (Skees et al., 2007; Hazell et al., 2010). Literatures report lack of insurance participation (Giné et al., 2008). In addition to that, if the financial and technical assistance ends long before demonstrating the viability of these programmes, the insurers might be discouraged to continue. Moreover, since weather related losses are covariate, meaning they affect large areas at the same time, after a couple of set backs the insurers might also find it difficult to continue without financial and technical assistance. Therefore, it is logical to infer that this lack of push from the insurers might be an additional reason for post-pilot discontinuity of these products.

This chapter shows how long it takes an average weather derivative to pay-off its initial investments and running costs and start yielding returns for the insurers. This simple indicator (for details on Pay-Off period analysis please refer to Brandes and Odening, 1992) should give an idea whether the present pilot programmes are sufficient or not. The stake holders are not being advised on how many policies they should sell in order to break-even. Not that it is unimportant, but it is a matter of business planning once the insurance is in place. Instead, they are informed on the possible outcomes under different scenarios, which they should take into consideration during the planning phase. Additionally, it should aid insurance providers, donors as well as policy makers in their decision making process.

For example, policy makers and donors could better span the pilots, the requisite technical and financial assistance. Grants or loans to design and promote these products could be adequately priced. Depending on the scenario that best represent their case (from the list being presented), they could also decide whether to promote weather derivatives as a stand alone product or couple it with agricultural credit (Skees and Barnett, 2006), in case the pay-off period is too long to sustain it as a stand alone product.

For insurance providers, this is informative since they get an alternate view of what they are getting into. Depending on the market demand they expect, and the initial cost of designing these products, they can better estimate when they might break-even. Moreover, they can better negotiate the duration of financial and technical assistance, subsidies and policy environment required for their involvement. Additionally it helps an insurer see how her decisions and negotiations with her reinsurer affect the pay-off period of her product.

After briefly introducing the products and the assumed demand trends Section 3.2 discusses the quota share reinsurance contract. In Section 3.3 the methodology is being discussed. Using this method on the set of data and assumptions as well as reinsurance parameters, the pay-off periods are simulated and the results derived. Finally the conclusion is presented with a caveat and an outlook.

3.2 Data and assumptions

For the analysis two weather derivatives from Nicaragua and Malawi were selected. The choice was driven by the fact that they operate under two completely different weather patterns. The loss ratio is quite low in Nicaragua and quite high in Malawi[1]. They cover two entirely different types of crops (tobacco and groundnut). Therefore, averaging their outcomes should offer the reader a generalised overview of an average weather derivative than two products from the same region covering the same crop.

3.2.1 The Nicaraguan product[2]

Since 2007, a public-private partnership has sought to develop and test an alternative approach to insuring weather related risks on Nicaraguan agriculture. The weather derivative contracts were offered by two insurance providers, INISER (Instituto Nicaragüense de Seguros y Reaseguros) and SEGUROS LAFISE S.A. (Arce, 2009). LAFISE provided these services for clients of the LAFISE Bank, under reinsurance cover from Paris Re, while INISER was covered by Partner Re (both reinsurance companies have merged eventually). The programme in Nicaragua is mainly aimed at commercial groundnut farmers. It covers three types of risks named: “A”, the risk arising from drought during the entire production cycle; “B”, the risk arising from excess precipitation during the entire production cycle; and “C”, the risk arising from excess water during the harvest period. The contract runs from sowing in July to harvest in December. The sowing dates are within the 1st and 31st of July with 5 days interval.

[1]Loss ratio usually lies around 60%, for more information on ratemaking and loss reserving please refer to Brown and Gottlieb (2001).

[2]Information provided is on the basis of expert interview with Mr. Pablo D. Valdivia, Consultant, The World Bank, 2011.

Provinces: In this study the operation is considered as a whole and the pay off period is based on the outcomes of four provinces namely: Managua, Villa 15 de Julio, Chinandega and Leon. The area insured in all the four provinces is assumed to be uniform up to a maximum of 500 ha each, totalling to 2000 ha. This uniformity of assumption is done to avoid unnecessary complication in this analysis and also because there is no evidence to believe otherwise. The sum insured per hectare is uniform across provinces, fixed at USD 834 increasing at 4% p.a.[3]

Premium: The premia, expressed as percent of the insured amount, depend upon the province and the sowing date (please refer to Table 3.2.1). The premia is averaged over the seven possible sowing dates. This too is done because there is no evidence of any particular date being more popular than the other.

Expected Payout: The mean putative indemnifications were calculated in percent terms (per hectare) on the basis of 50 years of rainfall data (1958 through 2007) using the burn rate method. According to Odening et al. (2007) this is a good estimation of the expected payout especially since long term rainfall data was available[4]. The values reported in Table 3.2.1 enable the reader a quick comparison between the premium and payout.

[3]Rate of discount was assumed to be World Bank lending rate (= LIBOR + 0.35%) as on 20th April 2012, rounded off to the next integer.

[4]The data and model required for the burn analysis was provided by Mr. Pablo D. Valdivia. However, the model can not be published since it is not permitted by the respective insurance providers in Nicaragua.

Table 3.2.1: Premia, expected payout and loss ratio of weather derivatives for groundnut

	PROVINCES			
SOWING DATE	MANAGUA	VILLA 15 DE JULIO	LEON	CHINANDEGA
Jul-01	5.31%	4.79%	9.08%	6.12%
Jul-05	5.31%	4.51%	7.67%	5.19%
Jul-10	5.31%	4.36%	6.61%	4.51%
Jul-15	5.31%	4.41%	5.91%	4.06%
Jul-20	5.31%	4.61%	5.55%	3.85%
Jul-25	5.40%	4.98%	5.55%	3.89%
Jul-30	5.65%	5.51%	5.91%	4.16%
AVERAGE PREMIUM	5.37%	4.74%	6.61%	4.54%
EXPECTED PAYOUTS	0.36%	0.47%	0.59%	0.24%
EXPECTED LOSS RATIO*	28.56%	31.70%	30.66%	27.13%

** Drawing from Mahul and Stutley (2010, Glossary xx), the loss ratio is the proportion of the sum of payouts, administrative costs (15% of premium), marketing and acquisition costs (5% of premium) and the fee to the weather stations (1.77% of the premium) to the premium collected.*
Source: Data acquired from the Agricultural Risk Management Team of The World Bank and own analysis.

3.2.2 The Malawian product[5]

In Malawi the weather derivatives for tobacco portfolio of Opportunity International Bank of Malawi is taken into consideration. They primarily insured the crop against drought during growing stages and excess rainfall during harvest. They have been insuring their crop portfolio since 2007 by coupling them with the crop loans. The tobacco portfolio consists of Flue Cured Virginia (FCV) and Burley tobacco. The choice for tobacco was driven by the fact that other weather derivatives covering crops like groundnut was discontinued in 2007 due to operational issues.

Provinces: In this study the calculations are based on the tobacco portfolio in Kasungu and Mzuzu provinces. Also in this case, uniform allocation of area is assumed for each crop across the

[5] Information provided is on the basis of expert interview with Ms. Erin Bryla, Consultant, The World Bank, 2011.

provinces, so the area totals to a maximum of 2000 ha. The sum insured per hectare is uniform across provinces, fixed at USD 2050.00 for FCV and USD 1650.00 for Burley tobacco, increasing at 4% p.a.

Premium: The premia (expressed as percent of insured amount) differ across provinces and on the type of tobacco crop (please refer to Table 3.2.2).

Expected Payout: The expected payouts were calculated in percent terms (per hectare) on the basis of 47 years of rainfall data (1962 through 2008) using burn rate method[6]. The values are reported in Table 3.2.2.

Table 3.2.2: Premia, expected payout and loss ratio of weather derivatives for tobacco

	KASUNGU		MZUZU	
SEASON	FCV	BURLEY	FCV	BURLEY
2007/08	4.51%	4.70%	-	-
2008/09	4.51%	4.70%	4.51%	4.63%
2009/10	4.51%	4.70%	4.51%	4.63%
AVERAGE PREMIUM	4.51%	4.70%	4.51%	4.63%
EXPECTED PAYOUT	2.00%	2.07%	2.06%	2.12%
EXPECTED LOSS RATIO*	65.64%	65.32%	67.02%	67.05%

** Drawing from Mahul and Stutley (2010, Glossary xx), the loss ratio is the proportion of the sum of payouts, administrative costs (15% of premium), marketing and acquisition costs (5% of premium) and the fee to the weather stations (1.77% of the premium) to the premium collected.*
Source: Data acquired from the Agricultural Risk Management Team of The World Bank and own analysis.

3.2.3 Design costs

The initial cost of designing these products are quite high. This is mainly due to the fact that experts are not available locally and the products have to be designed specific to location and crop. The cost incurred by The Agricultural Risk Management Team of the World Bank (in US Dollars),

[6]The data and model required for the burn analysis was provided by Ms. Erin Bryla. However, the model can not be published since it is not permitted by the insurance provider in Malawi.

for designing and piloting the Nicaraguan and Malawian weather derivatives has been tabulated in Table 3.2.3.

Table 3.2.3: Initial design costs for the weather derivatives

YEAR	NICARAGUA	MALAWI
2006	$24,718	$34,634
2007	$49,214	$41,385
2008	$23,788	$82,036
2009	$46,215	$32,974
2010	$12,115	-
Total	$156,050	$191,029

Source: Agricultural Risk Management Team, The World Bank.

3.2.4 Demand trend simulations

Literature on demand for agricultural weather derivatives report the effect of price, trust and liquidity constraints (Cole et al., 2013). Additionally, marketing effort (Stein, 2011), payout statistics (Giné et al., 2007) and basis risk (Banerjee and Berg, 2011; Clarke, 2011) are reported to affect demand. In order to develop a demand trend based on the aforementioned factors, one needs long term data, which are clearly unavailable in these cases. But, this methodology is intended to be used as a tool at the planning phase, so the reader would not be having these data either. Therefore, instead of estimating demand, numerous scenarios are simulated.

In most literature on insurance demand models (Garrido and Zilberman, 2008; Giné et al., 2008), estimations are based on number of policies sold. This approach has not been adopted for three reasons. First, there is no long term data on participation statistics of these programmes (they have started in 2007). Second, in case of agricultural insurance the market performance of a product should be determined by the proportion of cultivated land being insured and not by the number of farmers participating. Third, all relevant data was available on a percent per hectare term.

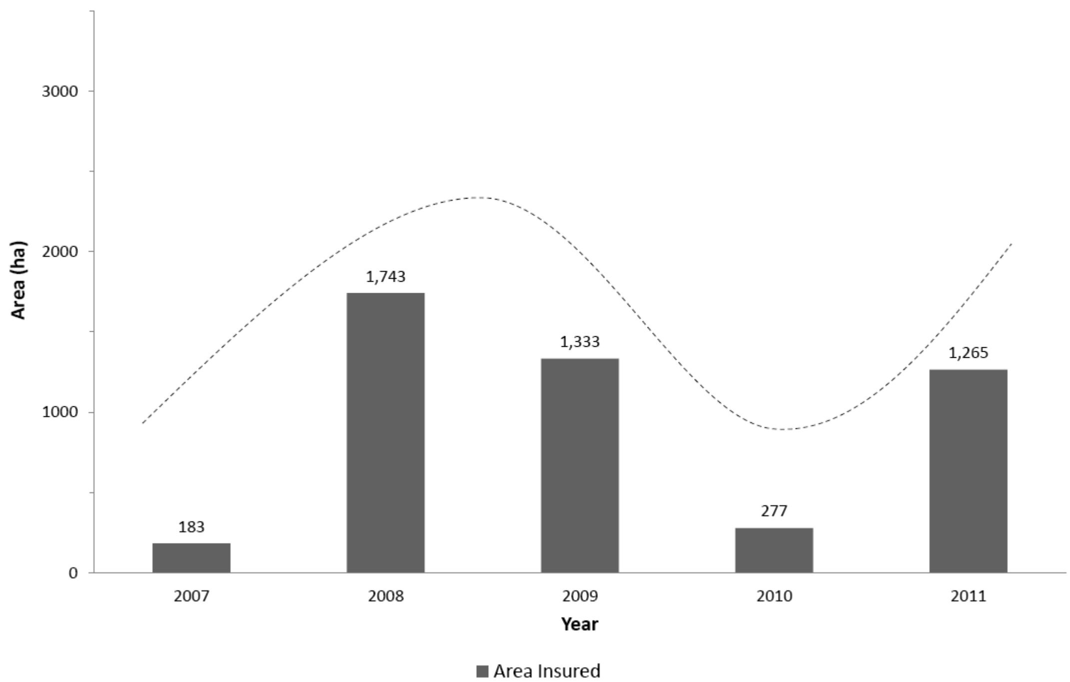
So, the area insured with respect to three different demand trends were simulated. The total area insured is capped at 2000 ha for both Malawian and the Nicaraguan product and is assumed to be uniformly distributed. In case of Nicaragua, since 4 provinces are dealt with, each province is programmed to have a maximum of 500 ha although the simulated outcomes among provinces differ. Similarly for Malawi, the FCV and Burley crops in both Kasungu and Mzuzu provinces are programmed to have a maximum allocation of 500 ha each. This uniform distribution was done because there is no evidence of any province of crop having any advantage over the other in terms of land allocation. Additionally, to avoid an unrealistically linear increase, decrease or smooth cycle, 30% randomness was introduced in the outcome.

Increasing demand: This function simply simulates outcomes where insured area increases over time at various rates. The outcomes are dependant on the initial area and the rate of increase and their various combinations constitute the different scenarios. 8 cases of initial area (from 100 ha to 1750 ha) and 10 cases of rate of increase (1-10%) totalling to 80 scenarios of temporally increasing demands were simulated. Although practitioners might argue that this type of demand trend is utopian in case of weather derivatives nevertheless, for an academic exercise it is worth considering.

Decreasing demand: This function simulates outcomes where insured area decreases over time at various rates. The outcomes are similarly dependant on the initial area and the rate of decrease and their combinations constitute scenarios. Here too, 80 scenarios of temporally decreasing demands were simulated. This is unfortunately what happens in reality to weather derivatives in most cases.

Cyclic demand: This demand trend was inspired by the facts observed in Nicaragua. The total area insured from 2007 through 2011 as reported by INISER, is shown in Figure 3.2.1. It clearly follows a cyclic pattern (shown by the dotted line), this stems from the strong influence of El Niño on Nicaraguan precipitation pattern and consequently agriculture. Due to this, farmers have varying expectations about weather outcomes and it affects their decision towards volume of cultivation and insurance purchase. This is an important piece of information that was built into this simulation so as to reflect a four year business cycle (as in case of El Niño).

Figure 3.2.1: Insured area in Nicaragua



Source: Own illustration based on data provided by officials of INISER, Nicaragua.

Although there is no data on effect of El Niño in Malawi, cycles do exist in markets. Those cycles are probably not for four years, but that could be counted as one scenario. Again as an academic exercise it was decided to observe the effect of a cyclic demand trend on the Malawian product too. The function as such, has a linear trend component, a sine function (to replicate the 4 year cycle) and 30% randomness. In this simulation, the area insured $\left[A_{l,t}\right]$, at a particular location $[l]$, at given period of time $[t]$, is constrained by:

$$A_{l,t} = \min(A_{l,t}^{sim}, A_l^{max})$$

where,

A_l^{max} : refers to the maximum area (500 ha) that might be insured at a given location.

$A_{l,t}^{sim}$: refers to the simulated insured area at a particular location at given period of time. Given by:

$$A_{l,t}^{sim} = \min\left[A_l^{in} + N^{min} + N + \sin(3t/2)\cdot(A_l^{in} + 2N^{min}), A_l^{in}\cdot(1+r)^t\right]$$

where,

A_l^{in} : refers to the initial insured area at a particular location on the first year of launching the scheme.

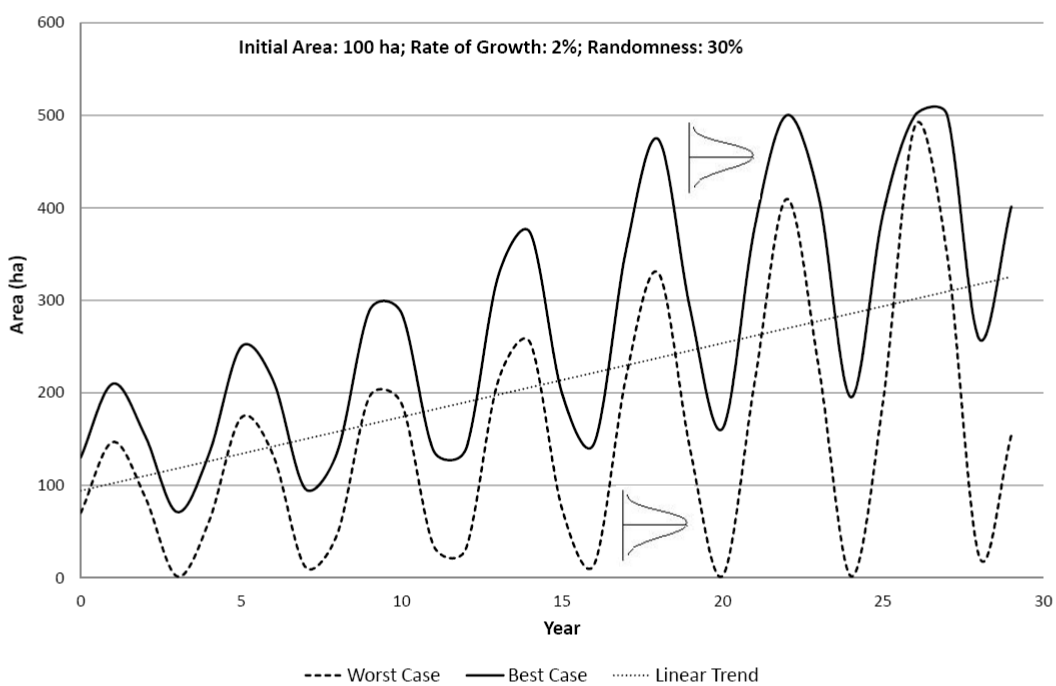
N : is a random integer within a minimum N^{min} and a maximum value of N^{max}.

$\sin(3t/2)$: is the sine function to generate a 4 year cycle in tandem with El Niño.

r : is the rate at which the area insured is planned to grow.

Although pay-off periods are not significantly affected, cyclic demands have an observable effect on the progression of quota share reinsurance parameters. A pictorial rendition of the simulation can be seen in Figure 3.2.2.

Figure 3.2.2: Insured area with cyclic demand



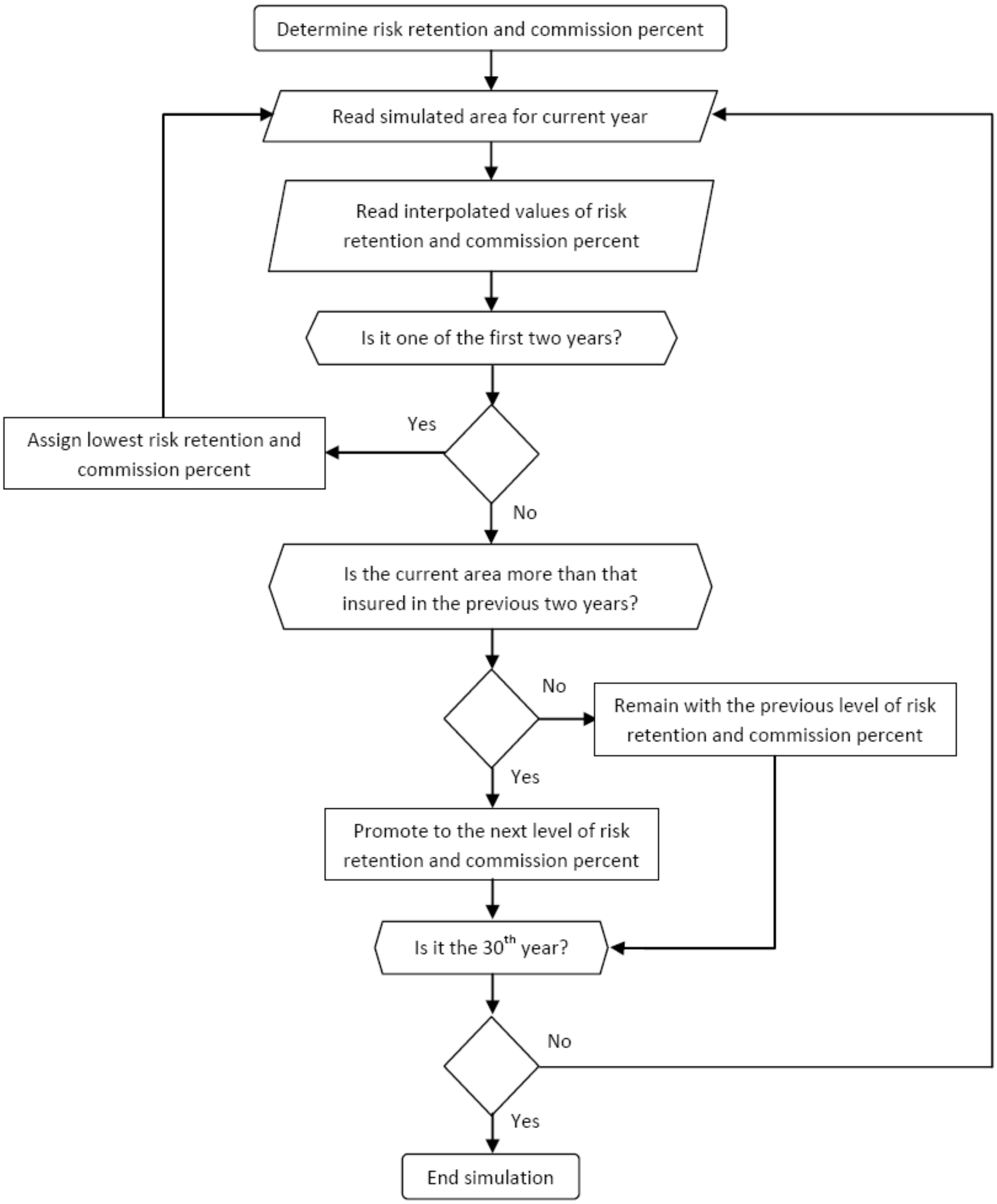
Source: Own illustration.

3.2.5 Quota Share Reinsurance

The insurers in these cases have a quota share contract with the reinsurer based on which, the percent of retained risk and commission was modelled[7]. Quota Share Reinsurance refers to a pro rata reinsurance agreement under which the insurer and reinsurer agree to share a pre-determined portion of all insurance premium, and losses. In addition they decide on a commission which enables the insurer cover her fixed costs. So if the insurer retains R% risk, she also retains that much premium and transfers the rest (100-R)% to the reinsurer. The commission is calculated on the basis of the later, so if they decide for a commission of C%, it means the insurer will get C(100-R)% of the total premium as (risk free) commission from the reinsurer. The percent of retention and commission usually grow as the market matures and the insurer sells more policies consistently. So in the initial years they start with low percent of risk retention and commission which eventually grows as per the performance of the insurer.

[7] On the basis of expert interview with Mr. Ramiro Iturrioz, Consultant, World Bank, 2011.

Figure 3.2.3: Simulation flowchart for risk retention and commission



Source: Own illustration based on expert interviews.

The exact procedure followed by reinsurance companies as well as the parameters agreed in these cases are business secrets. Therefore, this model was based on the progression of insured area. As per expert interviews, the weather derivatives under discussion might have retained 5% of the risk in initial years, but this lead to the pay-off periods being longer than 30 years in most cases. Hence in this model, the risk retention percent is programmed to grow from 20% through 40% linearly over a period of 30 years. The commission is similarly programmed to grow from 25% through 35% of the premium transferred to the reinsurer. As explained in the flowchart in Figure 3.2.3, when the insurer sustains a growth in insured area for a period of two years, she qualifies for the next level of linearly interpolated value of risk retention and also for the next higher level of commission (for an example of linearly interpolated values, please refer to Table B.2.1 on page 110).

3.3 Analysis

Pay off period refers to the time required for the weather derivatives to recover its initial design and operational costs and start yielding returns. For that matter, one needs to calculate the future net cash flows. These discounted to their net present value (NPV) gives an estimate of the pay-off periods, which is the point in time the NPV just turns positive (Brandes and Odening, 1992). The pay-off period $[T_i^*]$ of a weather derivative $[i]$ is given by:

$$T_i^* = \min\left[T : \sum_{t=0}^{T} \{e_{i,t} - E(a_{i,t})\} \cdot (1+z)^{-t} \geq 0; T \geqslant 0\right]$$

The term T_i^* is dependant on, the expected cash outflow $[E(a_t)]$, the cash inflow $[e_t]$ and the interest rate $[z]$.

Expected cash outflow: is the sum of fixed expenditures such as: marketing and acquisition costs, administrative costs, and variable expense arising from the indemnity payouts. Marketing and acquisition costs refer to the costs incurred to train insurance agents, motivating clients, as well as the sales commission for the agents. This and the administrative costs are fixed at 5% and 15% of the gross premium respectively (Mahul and Stutley, 2010). In addition, the expected cash outflow comprise of:

$$E(a_{i,t}) = \left(C_{i,t}^{des} + C_{i,t}^{wstn} + C_{i,t}^{m\&a} + C_{i,t}^{adm}\right) \cdot (1+z)^t + E(payout_t^{\$})$$

where,

l : refers to the locations/ crops.

t : is the time period.

$a_{i,t}$: is the annual cash outflow for a particular weather derivative.

$C_{i,t}^{des}$: refers to the initial cost of designing a particular insurance programme.

$C_{i,t}^{wstn}$: it is the cost of weather data. For Nicaragua, it is a sum of C$11000 per year paid to the state meteorological department INETER for the aforementioned stations. Based on an average of USD-C$ (Córdoba) exchange rate since 2003 this sum is assumed to be USD 583 increasing at 4% for 30 years. For Malawi, it is the sum of the cost of setting up a weather station (USD 51,260) and the running cost of USD 657 (increasing at 4% for 30 years), only one tenth of which has been considered for the weather derivative programme.

$C_{i,t}^{m\&a}$: refers to the cost of marketing and acquisition assumed to be 5% of gross premium (Mahul and Stutley, 2010, Annex E, p: 171).

$C_{i,t}^{adm}$: refers to the administrative costs assumed to be 15% of gross premium (Mahul and Stutley, 2010, Annex E, p: 171).

$E(payout_t^{\$})$: refers to the expected payout in USD for the respective provinces/crops and is given by:

$$E(payout_t^{\$}) = \sum_{l=1}^{4} R_{l,t} \cdot E(payout_l^{\%}) \cdot S \cdot (1+z)^t \cdot A_{l,t}$$

where,

$R_{l,t}$: refers to the percent of risk retained by the insurer with reference to a quota share reinsurance agreement, for a particular location and year (refer to the Subsection 3.2.5 on page 65).

$E(payout_l^{\%})$: refers to the expected payout in percent terms (refer to the values in Table 3.2.1 on page 59 and Table 3.2.2 on page 60).

S : is the sum insured per hectare. For Nicaragua, it is uniform at USD 834. For Malawi, it is USD 2050 and USD 1650 for FCV and Burley respectively.

z : is the inflation rate also assumed to be 4%.

$A_{l,t}$: refers to the insured area at a given location in a particular year (refer to Demand trend simulations on page 61).

Cash Inflow: is the sum of the net premium retained and the commission received from the reinsurer. The reinsurance contract influences the volume of both inflows and outflows since it decides how much business remains with the insurer and how much commission she gets. The cash inflows for the respective derivatives were given by the formula:

$$e_{i,t} = \sum_{l=1}^{4} P_{i,l} \cdot (1+z)^t \cdot A_{l,t} \cdot \left[R_{l,t} + C_{l,t}(1-R_{l,t})\right]$$

where in addition to the variables already mentioned,

$e_{i,t}$: is the annual cash inflow for a particular derivative i.

$P_{i,l}$: refers to the average premium for a given scheme and location (refer to the values in Table 3.2.1 on page 59 and Table 3.2.2 on page 60).

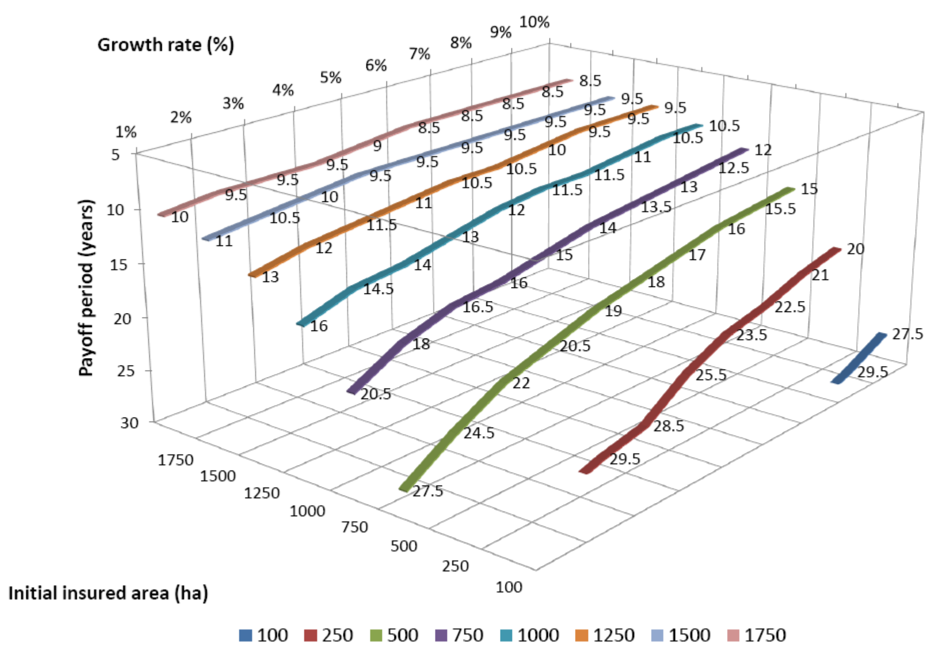
z : is the inflation rate also assumed to be 4%.

$C_{l,t}$: stands for the commission paid back to the insurance (refer to the Subsection 3.2.5 on page 65).

3.4 Results

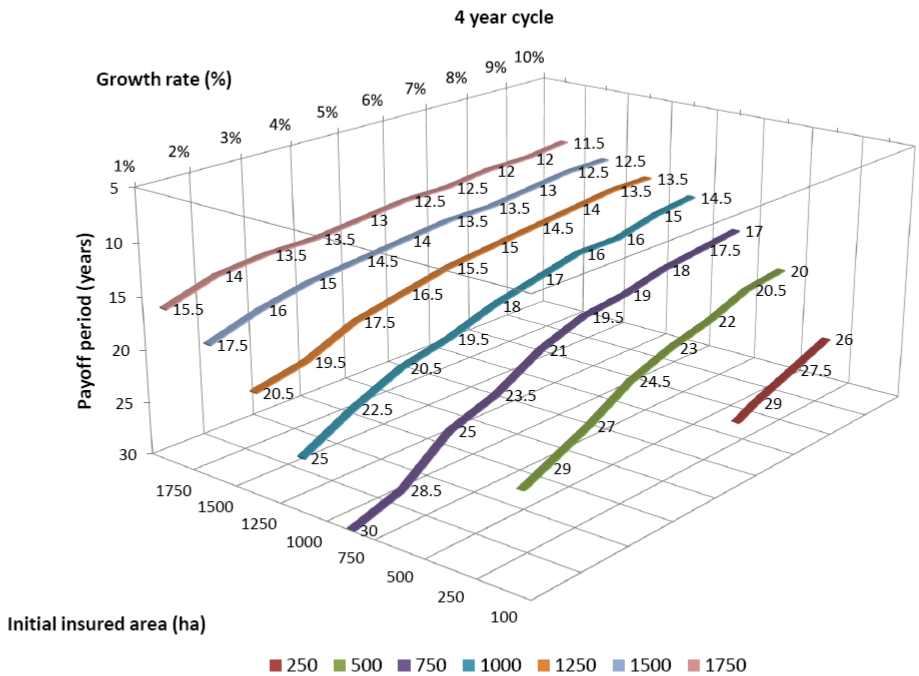
The average outcomes for both the weather derivatives for each type of demand trend have been presented in Figures 3.4.1, 3.4.3 and 3.4.2, so as to give the reader a general idea on the expected pay-off periods. Detailed overview have been presented in Figures B.1.1, 3.4.3 and 3.4.2 in the Appendix. A limit of 30 years is being set which means, scenarios under which the pay-off period exceeds 30 years have not been reported.

Figure 3.4.1: Pay-off periods with increasing demand



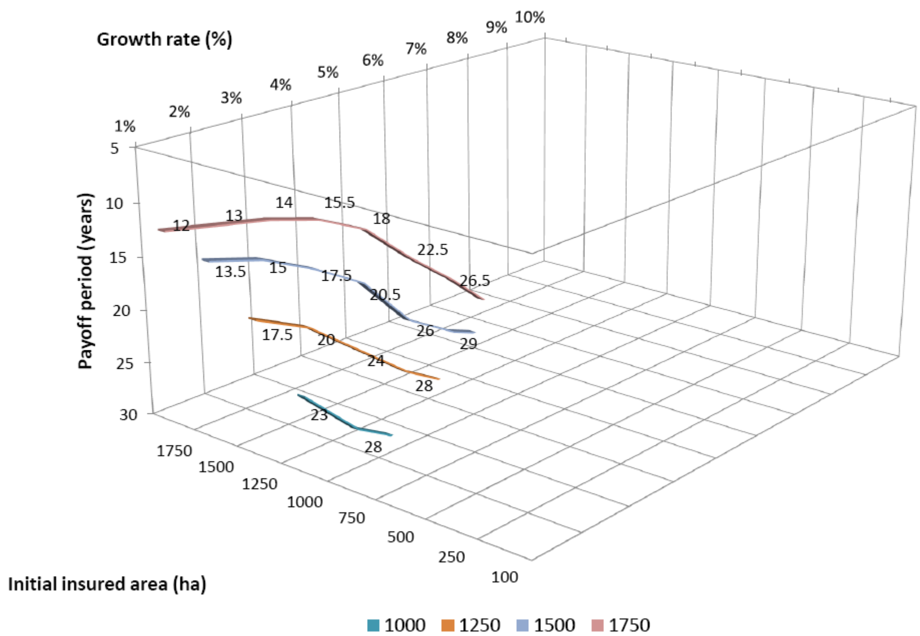
Source: Own analysis.

Figure 3.4.2: Pay-off periods with cyclic demand



Source: Own analysis.

Figure 3.4.3: Pay-off periods with decreasing demand



Source: Own analysis.

3.4.1 Expected pay-off periods

In the figures one can see the outcomes for 240 scenarios, 80 each for the three different demand trends, averaged for the Nicaraguan and Malawian weather derivatives. The results are based on assumptions and facts as previously discussed. As seen in Figures 3.4.1, 3.4.3 and 3.4.2, the results are quite informative. If one assumes increasing demand, with a realistic assumption of 750 ha initial area, planned to grow at 3% p.a., a weather derivative might take around 20 years to pay-off. For cyclic demand with similar values, the period is prolonged to around 22 years. Decreasing demand is clearly something the insurer should avoid and try to boost by coupling insurance with agricultural credit. In order to plan better, the insurer should therefore know her market and make realistic assumptions about the demand for her product. If a development organisation plans to promote these programmes, and is convinced of its need, the technical and financial hand holding should be of commensurate duration to convince the stake holders of its viability.

3.4.2 Reinsurance

As already mentioned, these results pertain to a reinsurance contract with risk retention of 20-40% (of the gross premium from area insured) and a commission of 25-35% (of the premium from the area re-insured). Scenarios with different reinsurance parameters were further estimated. Keeping the ceilings of the retention and commission percent as before (as per expert opinion those are the highest values a reinsurer would allow) the lower values in this model were increased from 5% to the upper limits (while following the rest of the process as explained in Subsection 3.2.5 on page 65). All other variables remaining constant, the data for cyclic demand trends were analysed. Table 3.4.1 shows the different combinations of risk retention and commission required for a weather derivative to pay off within 30 years and also the minimum initial area and growth percent required for that (expressed in the format X-Y %). The arrows simply imply that all the underlined combinations will result in a pay-off period shorter than 30 years.

The situation in case of the Nicaraguan weather derivative is explained by the loss ratio being around 30% (refer to Table 3.2.1). Commission is supposed to be a risk free payment from the

Table 3.4.1: Reinsurance conditions for pay-off within a 30 year window

RISK RETENTION	COMMISSION						
NICARAGUA	5%	10%	15%	20%	25%	30%	35%
5%			750-10%	→	→	→	→
10%		750-10%	→	→	→	→	→
15%	750-9%	→	→	→	→	→	→
20%	→	→	→	→	→	→	→
25%	→	→	→	→	→	→	→
30%	→	→	→	→	→	→	→
35%	→	→	→	→	→	→	→
MALAWI	5%	10%	15%	20%	25%	30%	35%
5%					1250-9%	→	→
10%					750-9%	→	→
15%					750-8%	→	→
20%				1000-9%	→	→	→
25%				750-9%	→	→	→
30%			1000-10%	→	→	→	→
35%		1750-9%	→	→	→	→	→

Source: Own analysis.

reinsurer to cover the fixed costs (20% of gross premium in these cases), whereas the premium retained is supposed to entail some risk. In the Nicaraguan case, the risk entailed by the retained premium is so low that even increasing the risk retention offsets the need for commissions. Therefore, even with 15 % risk retention, only 5% commission is required to cover the fixed costs and pay off within 29 years (with a total of 750 hectares of initial area growing at 9%).

In the case of the Malawian weather derivative, the loss ratio is around 65% (refer to Table 3.2.2). Therefore, the retained premium entails larger share of risk than the Nicaraguan one. Consequently, the insurer requires more commission to cover her fixed costs. Therefore, even for 25% of initial risk retention, a commission of 20% or more is required.

Higher retention means shorter pay-off period, but also lower commission, hence more risks and vice versa. In order to decide, one needs an additional look at the loss ratio. If the loss ratio is high, an insurer should count on the commission to pay for her fixed costs (as in case of the Malawian weather derivative). This means she should retain less risk, so that the risk free commission amount remains high. Conversely, if it is low (as seen in case of Nicaraguan weather derivative), retaining more risk and accepting lower commission would still lead to more cash inflows and hence faster pay-offs. However, downside risk associated with adverse weather outcomes (no matter how low), should be considered before framing such a reinsurance contract as should the financial endowment of the insurer be taken into consideration. These decisions should mainly be governed by the financial endowment of the insurer, based on this and the factors discussed above, she should decide on her retention and commission percent.

3.5 Conclusion

Although this analysis is case specific, a reader faced with a situation close to one of the many scenarios can make an educated guess as to how long a weather derivative might take to pay off (refer to Figure 3.4.1, 3.4.3 and 3.4.2). This should help the insurer decide the terms of the loan or grant and even the duration of technical assistance she would need. While negotiating reinsurance parameters, she should consider loss ratio as an important decision variable. As previously discussed, the insurer can decide whether to retain more risk and go for a faster pay-off or ask for more commission to cover her fixed costs. The methodology introduced, is simple and should be used at the planning phase to help frame the reinsurance parameters, subsidy and support, and scheduling of intermittent follow-ups and technical assistance.

Two cases of weather derivatives from Nicaragua and Malawi were considered in this study. The merits of weather derivatives as investment ventures has been analysed through estimation of pay-off periods. In order to do so, 240 scenarios have been simulated for each of the products in Nicaragua and Malawi. The scenarios were mainly based on demand trends which were simulated as increasing, decreasing and cyclic. In most of the cases the derivatives take around 30 years or more to pay-off. A quota share reinsurance contract was also simulated to elucidate the effects of different loss ratios and various reinsurance parameters on the pay-off periods.

For donors and policy makers, the implications are clear. Since weather derivatives take long to pay-off, a 3 to 5 year pilot is not sufficient. Weather derivatives are not promoted as profit making ventures, they often serve as a proxy to named or multi peril crop insurance, which can not be promoted due to reasons discussed in Section 3.1. So, if development agencies are convinced about the efficacy of weather derivatives as risk management and social development tools (Alderman et al., 2007; Alderman, 2008; Dercon, 2004), they should design their interventions adequately, to practically demonstrate the same. It has not been argued that the pilot should be as long as the product takes to pays off, but it should definitely be commensurate. If the intervention is financed by grant money, then it is not likely that the insurer will carry on with the programme in face of losses. She has no interest to recover the initial investment, if there is no technical or financial hand holding. In that case the invested time, effort and money are wasted. Conversely, if it is loan financed, it is the funder's money that is at stake. If a few more years of assistance could help recover the initial investment and start yielding returns for the insurer, it is worth a try. Despite the fact that additional intervention will bring up the costs further, it might result in a sustained intervention rather than a bad loan. Using this methodology and analysis, one could draw educated estimations as to how long such interventions might span.

From this analysis it is clear that initial costs and low risk retention due to systemic nature of weather risks are the main factors behind long pay-off periods. Additionally, demand trends play an important role. It is natural that increasing demand trends lead to shortening of the pay-off periods. Taking it as a hint one should find ways to increase demand for these products. Literature often discuss intrinsic factors like lowering basis risk and premium for boosting demand. It is advisable to look for extrinsic factors too. Micro-credits for farm enterprises have been successful in developing countries, with an ever increasing demand (Robinson, 2001). If weather derivatives are coupled with micro-credits and priced adequately, their demand problems might be mitigated.

In its present form, weather derivative is hardly an efficient tool of agricultural risk management. However, given its evident advantages over traditional crop insurance, work needs to be done to improve it. Certain caveats are: (i) Weather derivatives needs substantial initial investment in Research and Development (design) that most insurers might not be willing to undertake since there is no clear guarantee of scaling up. (ii) Since these costs are incurred in the initial years the pay-off period is prolonged as a result. (ii) The product will self-sustain only when it yields profits for insurance companies and manage to get enough volumes to keep the business interest of their re-insurers. Some close technical companionship will be needed as part of a weather derivative promoting program from the donor's side until the operations are streamlined. A longer-term planning of financial backing and technical assistance will go a long way in promoting these innovative risk management tools.

Chapter 4

Adversities of Adverse Selection

Abstract:

This paper discusses the possibility of inter-temporal adverse selection in weather derivatives. In regions affected by major weather events, whose effects may linger for months, farmers might base their insurance purchase decisions on weather outcomes of prior months. A methodology to estimate the effect of the resultant adverse selection on the insurers' reserve and identify the source of this information asymmetry is being presented. Since it is being argued that differential pricing is a sub-optimal strategy, the insurer should consider measures of rescheduling the contract. Proper ex-ante analysis in line with this proposal might help the insurer avoid some unpleasant surprises.

Keywords: Index based insurance; weather derivative; adverse selection; El Niño; insurance reserve

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4.1 Introduction

Weather derivatives may be generalized as forward contracts, and they normally occur as futures or as options. Although each kind of future transaction is possible, options dominate the market as they are particularly appropriate to reduce downside risks. In case of options, the buyer (long position) purchases a right and pays a premium for it, while the seller (short position) accepts the obligation and receives the premium (Berg et al., 2006). The difference to other options lies in the fact that the underlying of a weather derivative is not connected with financial or commodity markets. Underlying are weather indices like temperature, precipitation, solar radiation or wind velocity, which are neither storable nor tradable and therefore represent so called exotic underlying (Schirm, 2000).

Weather derivatives have been piloted and implemented in various forms in several countries over the last decade to hedge weather related risks in farm enterprises (Mahul and Stutley, 2010). Due to its design features, weather derivatives fare better with the problems of moral hazard and adverse selection, operation costs are low and payouts are determined faster as compared to conventional crop insurances. This is mainly because there is no need for loss assessment (Skees et al., 2007; Barnett et al., 2008). Since the payout is derived on the basis of weather outcomes and not yield, a farmer cannot tamper with the outcome which usually causes the problem of moral hazard in case of traditional insurances. Likewise, since weather is same for all in a region served by a single weather station, farmers do not have significant differences in weather risk, thereby mitigating the problem of spatial adverse selection. The case of inter-temporal adverse selections is however different.

Climate change is likely to increase the frequency of extreme weather events, like the El Niño Southern Oscillation (ENSO) (Diaz and Markgraf, 2000). Since ENSO is one of the most important planetary events that affect rainfall patterns and thereby the agricultural sector, it is a matter of scientific interest. Existing literature show strong impacts of ENSO events on rice production in India (Selvaraju, 2003); Indonesia (Naylor et al., 2001); the Philippines (Roberts et al., 2009) and Sri Lanka (Zubair, 2002). This also opens up opportunities for inter-temporal adverse selection as these weather patterns linger for an extended period of time and farmers can base their decisions on this prior information. Therefore, before an insurer introduces weather derivatives in such markets, it is advisable to check for the possibility thereof and also estimate the probable implications on the financial feasibility of the venture.

This chapter delves into the problem presented by inter-temporal adverse selection and its mitigation from the insurer's point of view. The next section, elaborates the concept of spatial and inter-temporal adverse selection with some examples. Thereafter the conjecture on how inter-temporal adverse selection could stem from major weather phenomena has been presented. The third section proposes a model for ex-ante estimation of the financial effect of inter-temporal adverse selection. Following that, mitigation measures are discussed and the conjecture explained through the case of rice crop grown in five states of the Indian Peninsula where possibilities of adverse selection in case of rainfall indexed weather insurance is being sought. A series of correlation analyses were performed to find statistically significant relationships between area cultivated in the two main seasons namely, Kharif (June through September) and Rabi (October through February), with respect to the incident rainfall. Finally, the conclusions are presented and ways to minimise the effect are discussed.

4.2 Inter-temporal adverse selection

In his seminal paper, Akerlof (1970) explains how information asymmetry and thereby resulting adverse selection disrupts market mechanisms. This is further discussed by Stiglitz and Weiss (1981) with focus on credit and labour market and Prescott and Townsend (1984) focussing on the insurance case, drawing from the findings of Rothschild and Stiglitz (1976). Adverse selection stems from information asymmetry. It is a situation whereby individuals with higher than average risk seek insurance while those with lower than average risks find it uneconomical (Doherty, 2000). The case of weather derivatives however, is different from that of conventional insurance. These derivatives are claimed to be free of adverse selection since weather is same for everyone in a region, and the characteristic randomness of weather makes adverse selection based on weather impossible for both insurer and insurance seeker. However, this refers to spatial adverse selection. Inter-temporal adverse selection is a different issue worth investigation.

Luo et al. (1994) explain "spatial adverse selection", as a phenomenon caused by using a geographic area as a risk-pooling group for crop insurance. For example, Just et al. (1999) demonstrate that to those farmers with no historical yield data, premium calculation of the Multiple Peril Crop Insurance (MPCI) is based on risk pooling over a county in the United States, while the indemnity is paid to an individual farm. As a result, farmers with a higher-than-county-average loss risk purchase insurance, while those with lower-than-county-average loss risk do not participate. Luo et al. (1994, p: 441) in their paper also identify the "inter-temporal adverse selection" and explain, "lntertemporal adverse selection refers to the behaviour of an insurance buyer selecting only high-risk periods to purchase insurance with no adjustments being made by the seller to reflect this behavioural pattern".

In regions affected by significant weather events like the El Niño, La Niña or the Indian Ocean Dipole, changes in weather patterns linger for an extended period of time. For example the March rain might already indicate what the October rains will be. If October marks the onset of the sowing season, farmers can already make their decisions based on March rains. When offered weather based insurance before the sowing season, these farmers would also base their decision on the clues presented in March. This indicates inter-temporal adverse selection because the information asymmetry arises from clues at different points of time which one of the parties might read better than the other. The case of weather derivatives for commercial groundnut farmers, marketed in Nicaragua makes the phenomenon of inter-temporal adverse selection even clearer.

There is a strong influence of El Niño on Nicaraguan precipitation pattern and consequently agriculture. This was seen in the growing seasons of 2009 and 2010. As seen in Figure 3.2.1 the cyclic demand for insurance in these seasons can be attributed to adverse selection and cognitive risk. Due to the extreme drought that affected the Central American region in 2009, the government through the Ministry of Agriculture and the National Met Service (INETER) broadcast in radio and

TV to alert farmers about possible negative effects of El Niño event on the agricultural sector. As a result many farmers, despite the financial crisis of 2008, purchased insurance for groundnut (and other crops like rice). Eventually, the rainy season in 2010 saw torrential downpours and the farmers thought – based on their past experiences – that 2010 cropping season was going to experience favourable rainfall patterns. This led to a drastic drop in insurance sales (refer to Figure 3.2.1 on page 63)[1]. The fact that the sales go up and down cyclically is not the main problem. The problem occurs when sales and payouts highly correlate with each other, as insurance companies cannot build up capital reserves any more.

The very design feature that mitigates spatial adverse selection in weather derivatives renders it vulnerable to inter-temporal adverse selection. The most commonly used method for designing and pricing weather derivatives is to simulate payouts based on historical weather data and calculate the expected payout. This gives the fair premium, based on which the commercial premium is calculated (Cao et al., 2003; Jewson and Caballero, 2003). Through this method, information on weather patterns are often lost. A classical example is CDD (cooling degree days) or HDD (heating degree days) based indices, where the loss of information is best described by permutation invariance.

Definition (Permutation invariant): Supposing a matrix $h(x,y) \Rightarrow \mathbb{R}$ where $x \in R^m$ and $y \in R^n$ where R^m and R^n denotes the vector space of real numbers of dimensions m and n. Then $h(.)$ is permutation invariant with respect to x if and only if $h(x,y) = h(\wp(x),y)$ for any x and y, $\wp(\cdot)$ being a permutation generating function.

Corollary: $CDD(T)$ and $HDD(T)$ are permutation invariant with respect to temperature index T.

Proof: $CDD(T)$ is defined as $\sum_{i=1}^{n} r\left[\max\{0,(T_i - d)\}\right]$, $r(\cdot)$ being a rounding function that returns the nearest integer, and d being the strike temperature (which is the long term daily average).

[1]Information provided is on the basis of expert interview with Mr. Pablo D. Valdivia, Consultant, The World Bank, 2011.

Supposing $\wp(T)$ returned $T^{'}$, then it is possible to find a matrix P such that $T^{'} = PT$. Now, since this matrix P has at least one 1 in each column and row, for a column unit vector e, $Pe = e$. From this the argument, one can derive:

$$\begin{aligned} CDD(T^{'}) =& e^T \cdot r[max\left\{0; (T^{'} - e \cdot d)\right\}] \\ =& e^T \cdot r[max\{0; (P \cdot T - e \cdot d)\}] \\ =& e^T \cdot r[max\{0; (P \cdot T - P \cdot e \cdot d)\}] \\ =& e^T \cdot P \cdot r[max\{0; (T - e \cdot d)\}] \\ =& e^T \cdot r[max\{0; (T - e \cdot d)\}] \\ =& CDD(T) \end{aligned}$$

This holds equally good for HDD, and is logical for such truncated distributions as CDD and HDD. Similarly, for rainfall index based weather derivatives, this argument hinges on the fact that cycles go unaccounted for in probability distributions. This issue is further discussed by Clarke et al. (2012, p: 12) in their section on "Ratemaking for Weather Based Crop Insurance", where they state, "It is commonly assumed that indexed weather insurance products are not subject to adverse selection against the insurer, as the insurer typically has access to long time series data that is at least as good as any information possessed by potential purchasers. However, this relies on the insurer making the best use of available data. If, as seems common across India, ratemaking procedures are statistically inefficient, insurers may be exposed to adverse selection." The conjecture on the circumstance whereby inter-temporal adverse selection takes place is based on this argument.

The Conjecture: In case of weather derivatives, if the farmer's decision to insure is always in her favour, i.e. if the amount of insurance she buys correlates to the amount of payout she gets, there is a possibility that she can pre-estimate the weather outcome from another weather related clue before buying the insurance and therefore select adversely against the insurer.

4.3 Financial implications

The conjecture discusses a correlation coefficient $\rho_{A,y}$, where A is the area insured and y is the payout per unit area insured. Assuming that the farmer insures the entire area she sowed, $\rho_{A,y}$ could be derived from historical data. If this correlation coefficient is found to be significant, this will affect the reserve $[R_n]$ of insurance portfolio. As mentioned earlier, in favourable years, when the payout is low and the company is expected to build reserves, the farmer will anticipate the same and buy less insurance. Whereas, in unfavourable years, sales will be high and so will be the payouts.

The effect of $\rho_{A,y}$ on the reserve of the insurance provider can be seen in the following derivation. R_n is the reserve an insurer accumulates by insuring A_i units of area, charging p premium (commercial), paying out y_i Euros per unit area insured, in year i, summed over n years. This can be expressed as:

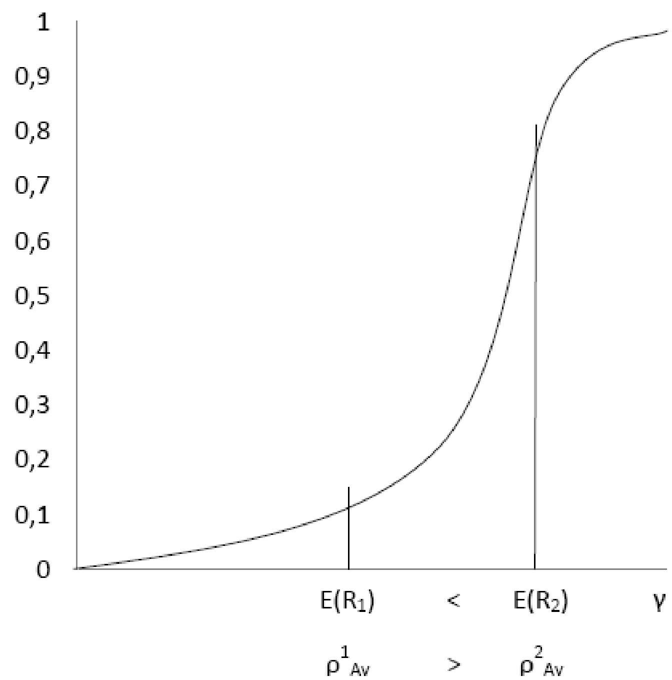
$$R_n = p\sum_{i}^{n} A_i - \sum_{i}^{n} A_i y_i \tag{4.3.1}$$

Now, in case of inter-temporal adverse selection, if A is correlated to y, such that correlation coefficient $\rho_{A,y} = \frac{E(Ay)-E(A)\cdot E(y)}{\sigma_A \sigma_y}$ or, $E(Ay) = \rho_{A,y}\sigma_A\sigma_y + E(A)\cdot E(y)$, where $E(.)$ denotes the expected value, one can derive:

$$\begin{aligned}
E(R_n) &= p\sum_{i}^{n} E(A_i) - \sum_{i}^{n} E(A_i y_i) \qquad (from 4.3.1) \\
&= p\sum_{i}^{n} E(A_i) - \sum_{i}^{n} \left[\rho_{A_i,y_i}\sigma_{A_i}\sigma_{y_i} + E(A_i)\cdot E(y_i)\right] \\
&= npE(A) - n\rho_{A,y}\sigma_A\sigma_y - nE(A)\cdot E(y) \\
&= n\left[E(A)\{p - E(y)\} - \rho_{A,y}\sigma_A\sigma_y\right] \\
or, \quad E(R) &= E(A)\{p - E(y)\} - \rho_{A,y}\sigma_A\sigma_y
\end{aligned} \tag{4.3.2}$$

where, $E(R)$ is the expected reserve an insurer accumulates in a year. This means, $\frac{\partial E(R)}{\partial \rho_{A,y}} < 0$ and it holds for linear relations between A and y.

Figure 4.3.1: Probability of ruin



Source: Own illustration.

This finding can be applied to the ruin theory (Powers, 1995) to derive further useful information. For simplicity of the following discussion, if one takes the payout $A \cdot y = \gamma$, the probability of absolute ruin is the probability that the payout $[\gamma]$ of the derivative is more than or equal to the reserve $[R]$. Since the point of absolute ruin is one when $\gamma = E(R)$, this is given by the probability $\Phi\{E(R) \leq \gamma\} = \int\limits_{E(R)}^{\infty} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{\gamma - E(\gamma)}{\sigma}\right)} d\gamma$. It is known from Equation 4.3.2 that when the correlation coefficient $\rho_{A,y}$ increases such that $\rho^1_{A,y} > \rho^2_{A,y}$, the corresponding expected reserve $E(R_1)$ and $E(R_2)$ decreases such that, $E(R_1) < E(R_2)$, the probability of ruin will increases such that, $\Phi\{E(R_1) \leq \gamma\} > \Phi\{E(R_2) \leq \gamma\}$. Taking a stylised Cumulative Distribution Function for the payout γ, (as seen in Figure 4.3.1) one can say:

$$
\begin{array}{rrcl}
 & \Phi[\gamma \le E(R_1)] & < & \Phi[\gamma \le E(R_2)] \\
\therefore & 1-\Phi[\gamma \le E(R_1)] & > & 1-\Phi[\gamma \le E(R_2)] \\
or & \Phi\{E(R_1) \le \gamma\} & > & \Phi\{E(R_2) \le \gamma\} \\
\because & \int\limits_{E(R_1)}^{\infty} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{\gamma-E(\gamma)}{\sigma}\right)} d\gamma & > & \int\limits_{E(R_2)}^{\infty} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{\gamma-E(\gamma)}{\sigma}\right)} d\gamma
\end{array}
$$

Therefore, with lower expected reserve the probability that the payout will exceed the insurers' reserve increases. The fact that $E(R)$ decreases with increasing $\rho_{A,y}$ is a result of the fact stated in the conjecture. In other words, the insurers' probability of ruin will rise with the farmers' predictive ability, given the insurers overlook the fact. Differential pricing will save the reserve from dropping but the market size will shrink and get adversely selected as discussed earlier.

4.4 Mitigation

Luo et al. (1994) recommend differential pricing whereby the premium is adjusted to the expected payouts. In case of MPCI it means farmers with higher than average risks pay more premium than the others. In the case of weather derivatives, this would translate to charging more premia in unfavourable years. However, they along with Skees and Reed (1986); Goodwin (1993); Miranda (1991) agree that over time this leads to higher premia and a more adversely selected market in case of MPCI. In case of weather derivatives, similar outcomes may be expected. Differential pricing might make weather derivatives too costly for cash constrained farmers in bad years and in good years it gives unnecessary signals of a favourable harvest, leading to dwindling demand. Therefore, the way out is to make the farmers enter into contract before the weather related clue presents itself.

Adverse selection stems from information asymmetry, in the case being discussed, it leads to the fact that the farmer and the insurer has two different subjective distribution of weather, F and I respectively. To mitigate inter-temporal adverse selection and thereby reduce the probability of ruin, the subjective distribution of weather for the farmer $[F]$ needs to become similar to the one of the insurer $[I]$. In their paper Just et al. (1999) discuss a similar situation albeit in context of Multiple Peril Crop Insurance in the U.S. In this thesis, an adaptation of their model has been presented in Chapter One. A detailed explanation of the particular case of adverse selection is to be found in Subsection 1.4.3 on page 28.

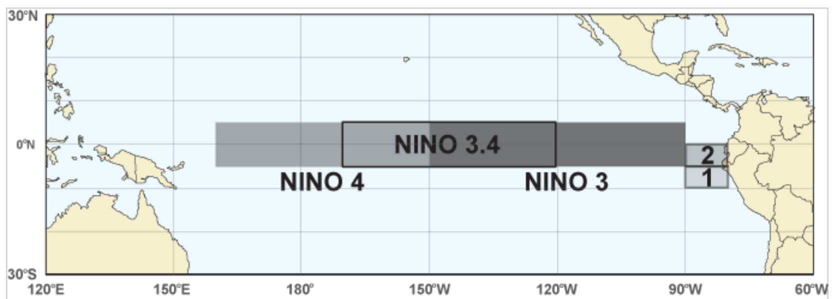
Equation 1.4.4 reflects the incentive that an insurance seeker derives from the opportunity of adverse selection. It is clear that once the two distributions F and I are same, so that there is no information asymmetry any more, the summand Δ_3 becomes zero and there is no possibility of adverse selection any more. In the case of inter-temporal adverse selection, this translates to finding a point in time when the farmer receives a weather related clue, cause before that, F and I are same and there is no possibility of adverse selection. In the following section, a method is proposed for finding that point in time, based on data for rainfall and cultivated area of rice in Southern India, a region reportedly affected by El Niño Southern Oscillation (Selvaraju, 2003).

To test this, rainfall in prior seasons and cultivated area in the subsequent seasons are required to find out whether the farmers decide on their sowing area $[A]$ in subsequent season(s) based on the rainfall $[Rn]$ of a prior month or not. Once a significant correlation $\left[\rho_{A,Rn}\right]$ is found, one needs to find out whether this information correctly mirrors the expectations. For that, it is checked if there is a similar significant correlation $\left[\rho_{A,y}\right]$ between the sown area $[A]$ in a season and the payout $[y]$ from the particular weather derivative in that same season. If it is the case, then it could be safely surmised that when offered insurance, the farmers will exercise this knowledge reflected by the measure $\rho_{A,Rn}$ and select adversely, unless measures are taken. So it is advisable to identify the month on which they base their decision and sell them the insurance before that. Of course the other alternative is differential pricing, but as discussed earlier, it would lead to a skewed market.

4.5 Identification of source

For the purpose of this paper, the effects of El Niño Southern Oscillation on rice cultivation in the South Indian Peninsula are being discussed. As seen in Figure 4.5.1, an El Niño phenomenon in the 3.4 region caused by Sea Surface Temperature Anomalies, affects rainfall patterns and therefore agriculture in India (Selvaraju, 2003).

Figure 4.5.1: Niño 3.4 region



Source: BOM (2012).

It is hypothesised that if farmers have this information they would reflect it in their cultivation decisions. For example if good March rains meant bad October rains, they will sow less to avoid losses and vice versa. This is an easily identifiable behaviour. Binswanger et al. (1993) for example, report how Indian farmers avoid risk by sowing low return crops in smaller manageable plots, which require low investment and allows greater control in the face of adversity. From this, one could argue, when offered insurance they would adversely select against the insurer. This section demonstrates a method to identify a point of time when the farmers' and insurers' information on impending weather pattern is symmetric. It is being argued that if the insurer enters into contract before this point of time, she will mitigate any risk of inter-temporal adverse selection. For that matter, one needs to find if there is a significant correlation between the rainfall and sown area in subsequent season(s), in five states of South India.

4.5.1 Data collection

Data on Area cultivated with rice was provided by the Food and Agricultural Organisation (FAOSTAT, 2010). Precipitation data was obtained from the KNMI Climate Explorer (KNMI, 2010). The Coordinates given were: 22.00N: 8.00N, 72.00E: 87.00E. Only the stations in Indian peninsula with at least 60 years of data (1950-2010) were considered and the ones without recent precipitation data were rejected. Twelve stations with the complete data sets in the five respective states were:

1. Maharashtra: (a) Akola (b) Pune (c) Mumbai (d) Nagpur.
2. Karnataka: (a) Bangalore (b) Belgaum.
3. Kerala: (a) Thiruvananthapuram (b) Calicut.
4. Tamil Nadu: (a) Chennai (b) Kodaikanal.
5. Andhra Pradesh: (a) Hyderabad (b) Masulipatnam.

4.5.2 Methodology

The time series of area cultivated with rice in the five aforementioned States are depicted in Appendix C.1 on page 111. The data so obtained were first de-trended using three methods discussed hereafter. The de-trending was followed by a correlation analysis to elucidate plausible relation of prior rainfall $[Rn]$ in the different states and its corresponding effect on area cultivated $[A]$ with rice. The plausible and significant relations thus revealed by the correlations could be further investigated by finding the correlation of the cultivated area and the tentative payouts to give an ex-ante estimate of the financial effect of adverse selection as discussed in Section on page 84.

De-trending: In order to filter the data of any existing trend, three distinct methods were used owing to their varied ability of conserving the variance of the population. The de-trending methods were as follows:

1. First differences, in lines of Naylor et al. (2001): The area cultivated in season s and year t minus that in season s and year $t-1$ $[A_{s,t}–A_{s,t-1}]$.

2. Deviation from a five year centred moving average (as in Zubair, 2002): A centred five year moving average $[C5MA]$ of cultivated area in season s was calculated. Then the percentage deviation of area in season s from the $C5MA$, $[(A_{s,t}–C5MA_{s,t})/C5MA_{s,t}]$ in each year was derived for better comparability. The percentage deviation was preferred because the trend in the absolute deviation will probably be high given the large increases in production over time in most developing countries due to the green revolution of late 60's, early 70's.

3. Normalized deviation from a third order polynomial trend (as in Roberts et al., 2009): Area in season s on time, time squared and time cubed i.e. a third order polynomial regression was calculated. Then the residuals $[Rd]$ from that regression were divided by the fitted values $[Fv]$ from the same regression, $[Rd_{s,t}/Fv_{s,t}]$. Dividing by the fitted value was preferred for the same reason as dividing by the $C5MA$ in the previous method.

Correlation analysis:

1. Correlation of first differences, as in Naylor et al. (2001): Correlate first differences in cultivated area $[A_{s,t}–A_{s,t-1}]$ with first differences in rainfall $[Rn_{m,t}–Rn_{m,t-1}]$, with appropriate lags. For each season s, the change in area was correlated with the change in rainfall for each of the 12 prior months m.

2. Correlation of deviation from a five year centred moving average, as in Zubair (2002): One drawback of this method is that it can't be used for predictive purposes, as one does not have future data on area. Nevertheless, it is still a useful method for analysis. The percentage deviation from centred moving average was correlated with rainfall in month m and year t, with appropriate lags, $[(A_{s,t}–C5MA_{s,t})/C5MA_{s,t}]$ with $[Rn_{m,t}]$ over time for each season s and month m. For each season s, the percentage deviation of area was correlated with rainfall for each of the 12 prior months.

3. Correlation of normalized deviation from a third order polynomial trend, as in Roberts et al. (2009): Correlated the percentage deviation of cultivated area from polynomial trend with rainfall in month m and year t, with appropriate lags, $[Rd_{s,t}/Fv_{s,t}]$ with $[Rn_{m,t}]$ over time for each season s and month m. For each season s, the percentage deviation of production was correlated with rainfall for each of the 12 prior months.

Statistical significance: The statistical significance of the correlation coefficients was ascertained by two sided student's t-test for Pearson's Product Moment Correlation Coefficient $[\rho]$, with N as the number of variable pairings. Given by the statistic:

$$t = \rho\sqrt{\frac{N-2}{1-\rho^2}}$$

The statistic t is asymptotically standard normal at null hypothesis $H_o : \rho = 0$. From this, the correlation coefficients significant at 10% were adopted for further analysis. As is evident from the aforementioned methodology, due to the three different methods of de-trending applied in this study, three distinct correlation matrices were obtained for every case.

4.5.3 Results

As an example, Table C.2.1 shows the results for the state of Andhra Pradesh. In the table, only those relations between rainfall in a particular month and sown area in subsequent season(s) have been highlighted, which have statistically significant (at 10% level of confidence) correlation coefficient (for all three de-trending methods). Since three different methods of de-trending was employed, only those coefficients which showed significance (at 10%) on all three counts are in bold characters and considered for further discussion.

Table 4.5.1: Significant relations between rainfall and sown area in Andhra Pradesh

	Andhra Pradesh			
	Sown area in seasons			
Rainfall in months	Kharif (t)	Kharif (t+1)	Rabi (t)	Rabi (t+1)
Jan		(-)	(-)	
Feb	(+)			
Mar				(+)
Apr				
May				
Jun	(+)	(-)		
Jul	(+)			
Aug	(+)	(-)		
Sep	(+)			
Oct				
Nov				
Dec		(+)		

Source: Own analysis.

The results of all the other regions (Maharashtra, Kerala, Karnataka and Tamil Nadu) can be found in Appendix C.2.1. The analyses clearly show that the states of Maharashtra, Andhra Pradesh, Kerala and Karnataka might have a possibility of information asymmetry while Tamil Nadu apparently shows no such possibility. For example in Table 4.5.1, one sees that in Andhra Pradesh, July, August and September rains affect the sown area in the Kharif season of the same year. However, this is trivial since it is understandable that the farmer plants more when it rains favourably in the sowing season beginning July. This does not prove any predictive ability on the farmers' part and hence can not lead to adverse selection. Conversely, the fact that June rains negatively correlate to the area cultivated by farmers in the Kharif season of next year is interesting as it is an indication for information advantage.

In Karnataka, September rains positively correlate to the area cultivated in Rabi season of the same year (Appendix C.2.1). In Kerala, rains in March, July and August have positive correlation to cultivated area in the Rabi season of the same year. In Maharashtra, September rains show positive correlation to the area cultivated in Rabi season of the same year. This point out a possibility that the farmers might base their cropping decision on the signals they receive in previous months.

In total, it appears that farmers in the different regions gain information on impending weather patterns during important cropping seasons earlier on. This might influence their decisions while purchasing insurances, which the insurers need to know before entering a market. Now that one has the value of $\rho_{A,Rn}$ and the point of time when the information asymmetry starts, the next step is to find $\rho_{A,y}$ through burn method to simulate the payout of the derivative in question. Once this statistic is estimated, the insurer can calculate the tentative effect on expected reserve (as shown in Equation 4.3.2) as well as the probability of ruin and decide on how to go about restructuring the derivative contract.

4.6 Conclusion

Weather derivatives might have comparatively lower spatial adverse selection, but in terms of inter-temporal adverse selection, the problem may be as pertinent as in case of traditional crop insurance. The chapter addresses this seldom discussed issue. In regions affected by major climatic events like El Niño Southern Oscillation, La Niña or the Indian Ocean Dipole, weather patterns linger for an extended period of time whereby, the farmers might be able to predict the outcomes in cropping seasons based on signals they read months in advance. In such cases, they might select adversely if offered insurance, indicating inter-temporal adverse selection. This probable adverse selection resulting from an information asymmetry is in line with the conjecture presented in this chapter. It has also been demonstrated that the design characteristics and common methods of ratemaking of a weather derivative, which protects it from spatial adverse selection, renders it vulnerable to inter-temporal adverse selection.

To address these issues, literature commonly propose differential pricing based on the insurers' analysis (Luo et al., 1994; Skees and Reed, 1986). The problem with differential pricing is that, in unfavourable years, when the premium is raised, it might get out of reach of poor farmers. On the other hand in favourable years, bringing down the premium might unnecessarily signal the farmer to abstain from buying insurance, thereby promoting adverse selection. The solution lies in rescheduling the contract date before the clue presents itself. For that matter, it is important to quantify the financial effect of adverse selection, since it might not be serious enough to warrant restructuring of the contract. A new method has been proposed to quantify the effect of adverse selection on the insurers' reserve. The expected reserve of an insurer decreases as the predictive ability of the insurance seeker increases. Since there is a possibility to assess this predictive ability from historical data, the insurer could easily estimate the financial implication ex-ante. With this information in hand, the insurer might subjectively decide weather it is worth her while to restructure the product or is it mild enough to be overlooked.

Since differential pricing is clearly a suboptimal strategy, entering into contracts before the clue presents itself, is a logical way out. However, this requires identification of the point of time when the clue presents itself. A method to identify the source(s) of information asymmetry has therefore been proposed. Based on historical data for rainfall and area cultivated, significant correlations with appropriate time lags may be identified. The case of rice crop in Southern India has for that matter been demonstrated. Once a statistically significant correlation is found between the rainfall in a month(s) and the area cultivated in a subsequent season(s), the insurer should estimate the financial implication of this apparent information asymmetry and contemplate offering the weather derivative at the earliest month. This prevents the market from getting adversely selected. Additionally, since the premia are collected months in advance, the insurer could easily offer it at a discount thereby boosting participation.

However, since the model uses Pearson's product moment correlation coefficient, it is sensitive to linear relations only. Therefore, it is necessary to base the decisions on the expected reserve, rather than jumping to conclusion based on correlations between prior rainfall pattern and cultivated area alone. The model presented should be furthered through ex-post empirical data from existent weather derivatives and hence calls for further research. Once streamlined, this methodology might help insurers avoid unpleasant surprises, as seen in the case of Nicaragua.

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Appendix A

Annex to Chapter 2

A.1 Size of Typhoons

Depending on the region of origin, if winds reach 33 m/s (74 mph), then the tropical cyclones are called: a. “Hurricane” (in the North Atlantic Ocean, the Northeast Pacific Ocean East of the dateline, or the South Pacific Ocean East of 160E) b. “Typhoon” (in the Northwest Pacific Ocean West of the dateline) c. “Severe tropical cyclone” (in the Southwest Pacific Ocean West of 160E or Southeast Indian Ocean East of 90E) d. “Severe cyclonic storm” (in the North Indian Ocean) e. “Tropical cyclone” (in the Southwest Indian Ocean). (Neumann, 1993)

Table A.1.1: Sizes of Tropical Typhoons

Distance (km)	Distance (nm)	Size / Type
¡ 220	¡ 120	Midget
220 - 335	120 - 180	Small
335 - 665	180 - 360	Medium
665 - 890	360 - 480	Large
¿ 890	¿ 480	Very Large

Source: Conversions based on Merrill (1984).

Tropical Cyclones or Typhoons are measured radially outward from the centre to the outermost closed isobar or to the lowest maximum sustained winds (1 or 10-min average) of 55 km/hr or 30 knots.

Table A.1.2: Typhoon classes on the Saffir-Simpson Scale

Category	Winds (km/h)	
	min	max
1	118	153
2	154	177
3	178	209
4	210	249
5	250	-

Source: Conversions based on NOAA (2012).

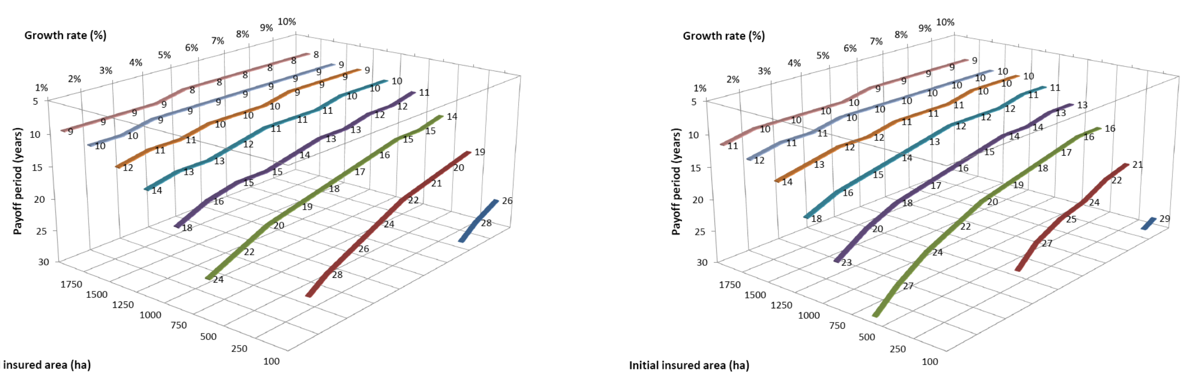
Appendix B

Annex to Chapter 3

B.1 Demand trends and pay-off periods

Figure B.1.1: Pay-off periods with increasing demand

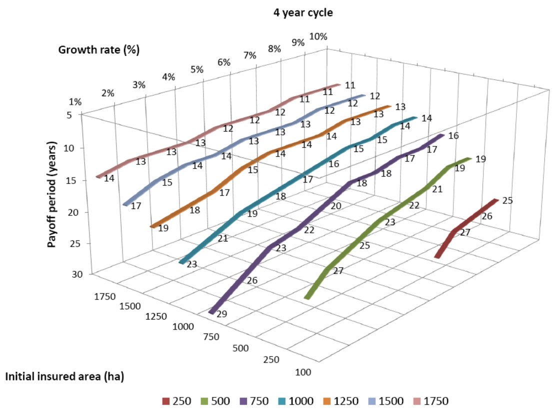
(a) Nicaragua (b) Malawi



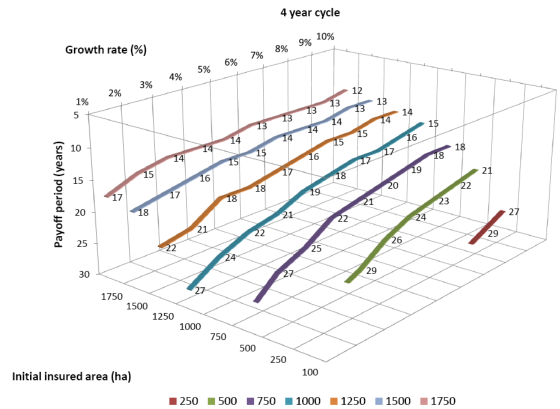
Source: Own analysis.

Figure B.1.3: Pay-off periods with cyclic demand

(a) Nicaragua



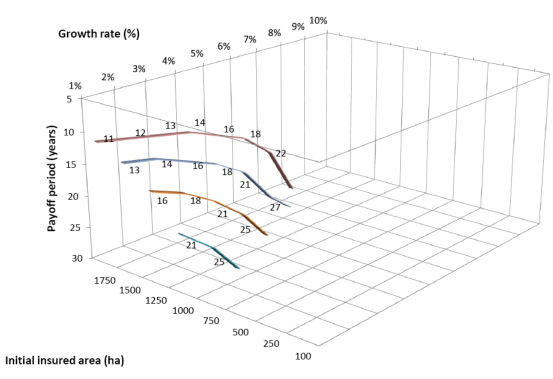
(b) Malawi



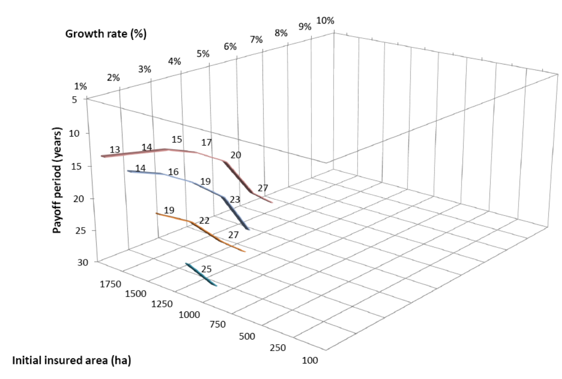
Source: Own analysis.

Figure B.1.2: Pay-off periods with decreasing demand

(a) Nicaragua



(b) Malawi



Source: Own analysis.

B.2 Interpolation of quota share reinsurance parameters

Table B.2.1: Interpolation of risk retention and commission for Chinandega

YEAR	SIMULATED AREA (ha)	INTERPOLATED RISK RETENTION	INTERPOLATED COMMISSION	RESULTANT RISK RETENTION	RESULTANT COMMISSION
0	425.00	20.00%	25.00%	20.00%	25.00%
1	500.00	20.69%	25.34%	20.00%	25.00%
2	500.00	21.38%	25.69%	20.69%	25.34%
3	103.01	22.07%	26.03%	20.00%	25.00%
4	426.93	22.76%	26.38%	20.00%	25.00%
5	500.00	23.45%	26.72%	20.69%	25.34%
6	500.00	24.14%	27.07%	21.38%	25.69%
7	74.75	24.83%	27.41%	20.69%	25.34%
8	408.33	25.52%	27.76%	20.00%	25.00%
9	500.00	26.21%	28.10%	20.69%	25.34%
10	500.00	26.90%	28.45%	21.38%	25.69%
11	296.38	27.59%	28.79%	20.69%	25.34%
12	306.38	28.28%	29.14%	20.00%	25.00%
13	500.00	28.97%	29.48%	20.69%	25.34%
14	500.00	29.66%	29.83%	21.38%	25.69%
15	500.00	30.34%	30.17%	22.07%	26.03%
16	139.20	31.03%	30.52%	21.38%	25.69%
17	500.00	31.72%	30.86%	22.07%	26.03%
18	500.00	32.41%	31.21%	22.76%	26.38%
19	500.00	33.10%	31.55%	23.45%	26.72%
20	275.38	33.79%	31.90%	22.76%	26.38%
21	500.00	34.48%	32.24%	23.45%	26.72%
22	500.00	35.17%	32.59%	24.14%	27.07%
23	500.00	35.86%	32.93%	24.83%	27.41%
24	94.46	36.55%	33.28%	24.14%	27.07%
25	500.00	37.24%	33.62%	24.83%	27.41%
26	500.00	37.93%	33.97%	25.52%	27.76%
27	500.00	38.62%	34.31%	26.21%	28.10%
28	500.00	39.31%	34.66%	26.90%	28.45%
29	500.00	40.00%	35.00%	27.59%	28.79%

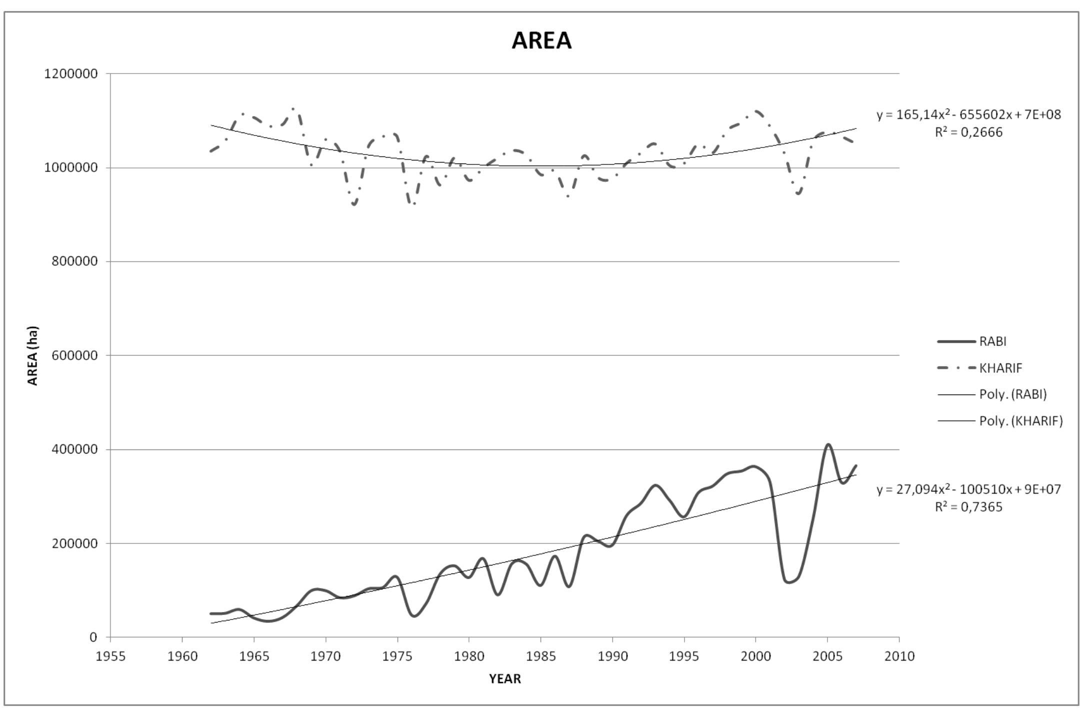
Note: Initial area: 500 ha; Growth rate: 5%; Percent randomness: 30%; Cycle: 4 years.
Source: Own analysis.

Appendix C

Annex to Chapter 4

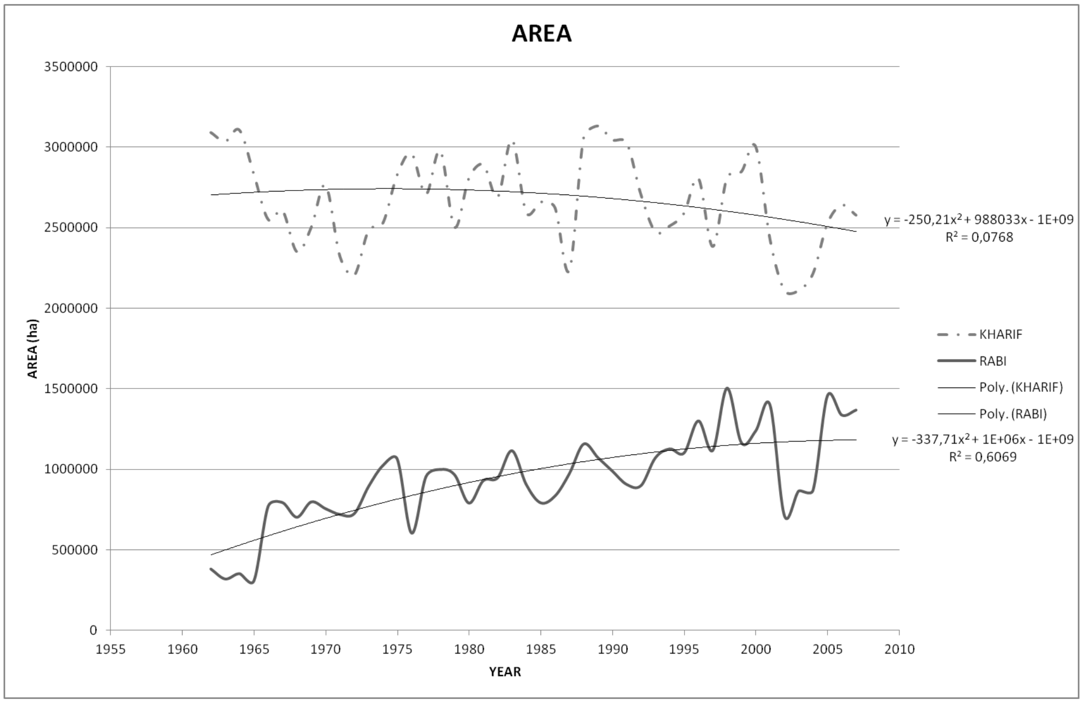
C.1 Time series of area cultivated with rice

Figure C.1.2: Cultivated area for rice in Karnataka



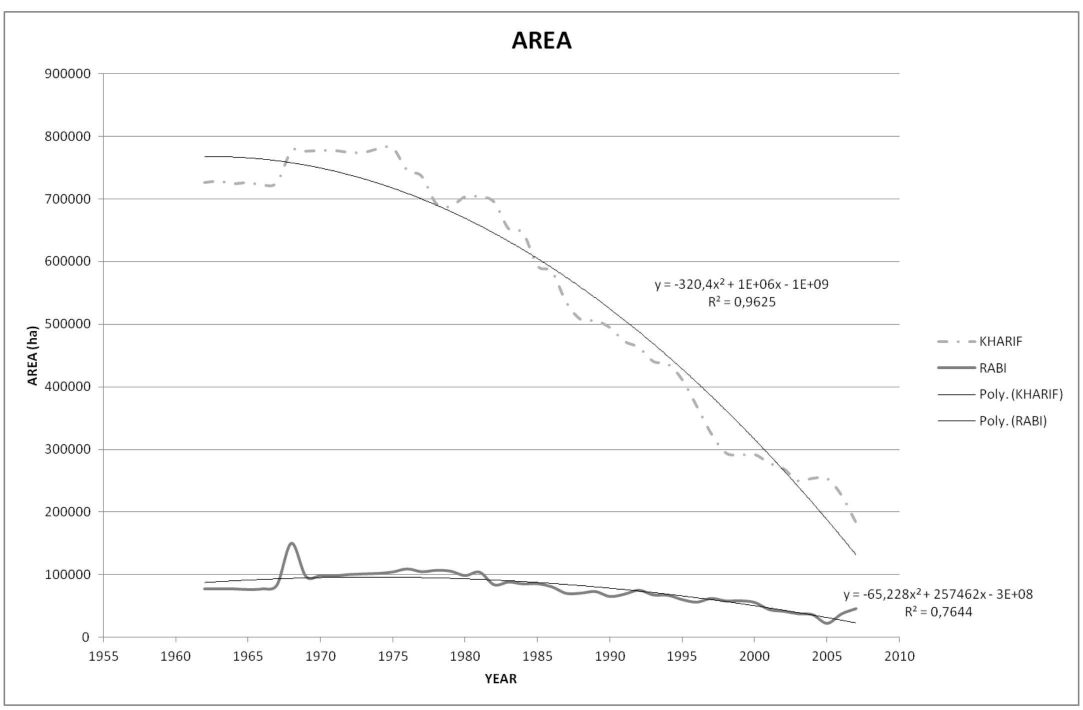
Source: FAOSTAT (2010) and own analysis.

Figure C.1.1: Cultivated area for rice in Andhra Pradesh



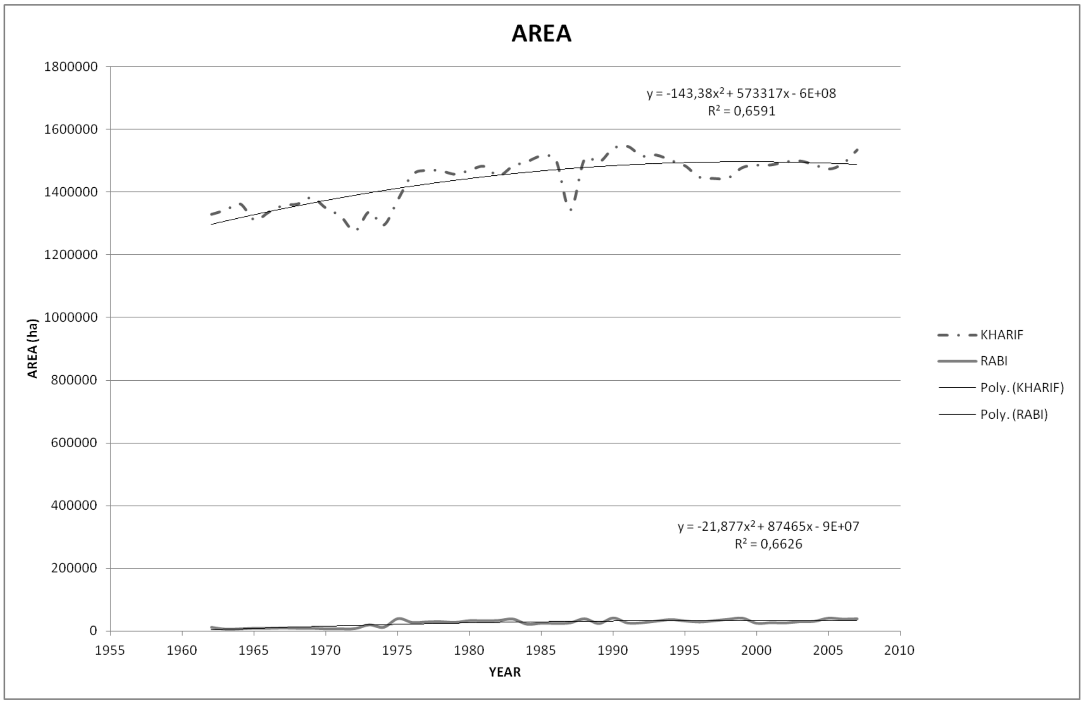
Source: FAOSTAT (2010) and own analysis.

Figure C.1.3: Cultivated area for rice in Kerala



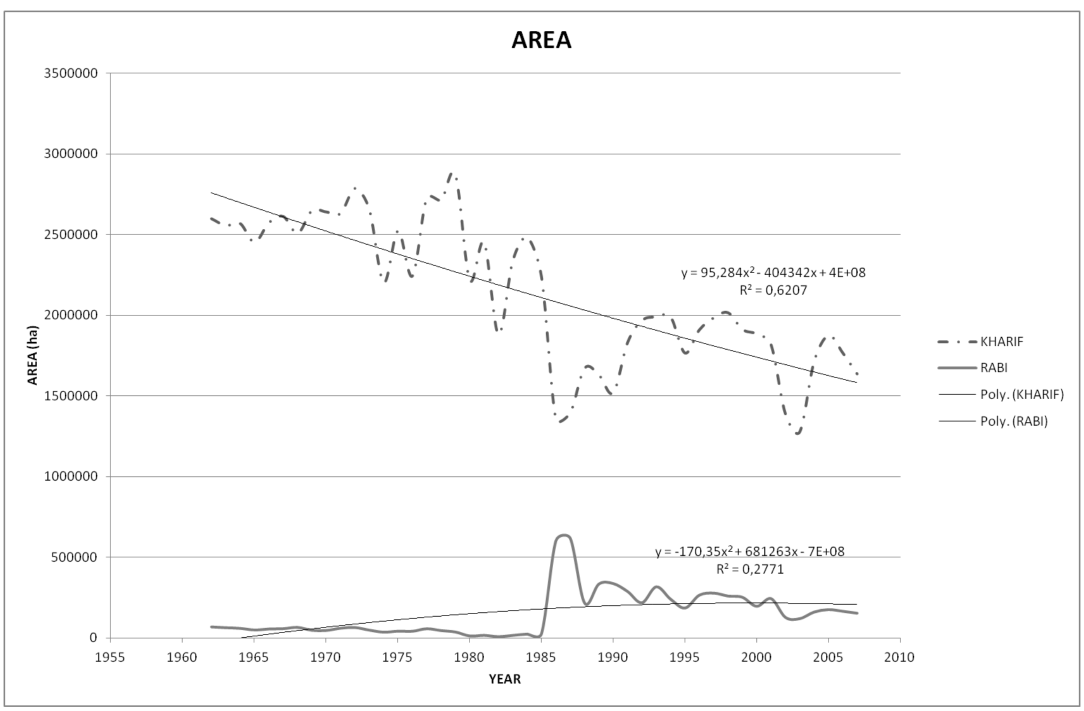
Source: FAOSTAT (2010) and own analysis.

Figure C.1.4: Cultivated area for rice in Maharashtra



Source: FAOSTAT (2010) and own analysis.

Figure C.1.5: Cultivated area for rice in Tamil Nadu



Source: FAOSTAT (2010) and own analysis.

C.2 Significant relations in other States

Table C.2.1: Significant relations between rainfall and sown area

	Karnataka				Maharashtra			
	Sown area in seasons				Sown area in seasons			
Rainfall in months	Kharif (t)	Kharif (t+1)	Rabi (t)	Rabi (t+1)	Kharif (t)	Kharif (t+1)	Rabi (t)	Rabi (t+1)
Jan								
Feb			(+)					
Mar					(-)	(+)		
Apr								
May				(+)			(+)	
Jun	**(+)**	(-)				(-)		(-)
Jul	(+)	(+)		(-)	(-)			(+)
Aug				(-)				
Sep	**(+)**	(-)	**(+)**	(-)			**(+)**	(-)
Oct					***(-)***	(-)	(+)	(-)
Nov	***(+)***							(+)
Dec	***(-)***						(+)	
	Kerala				**Tamil Nadu**			
Jan						(-)		
Feb					(+)		(+)	
Mar	(+)		**(+)**	(-)				
Apr	(+)					(-)	(+)	
May					(+)			
Jun								
Jul			**(+)**	(+)			(+)	
Aug			**(+)**				(+)	
Sep			(+)	(-)		(-)		(-)
Oct							(-)	
Nov							(-)	(+)
Dec	***(-)***		(-)	(+)	***(+)***			

Legend: Bold letters indicate the signs of statistically significant (at 10%) correlations found in all three de-trending methods, which are plausible. Bold italics indicate significant yet implausible correlations.
Source: Own analysis.