Chapter 9
Index-Based Risk Financing and Development of Natural Disaster Insurance Programs in Developing Asian Countries

Sommarat Chantarat, Krirk Pannangpetch, Nattapong Puttanapong, Preesan Rakwatin, and Thanasin Tanompongphandh

1 Introduction

There is growing evidence that the frequency and intensity of natural disasters continue to rise over the past decades (Swiss Re 2011a). This trend is likely to continue as the impact of climate change drives greater volatility in weather-related hazards (IPCC 2007). The low-income and developing countries suffered an increase of disaster incidence at almost twice the global rates large proportion of population still rely on agriculture and live in vulnerable environments (IFRCRCS 2011). Overall, costs per disaster as a share of GDP are considerably higher in developing countries (Gaiha and Thapa 2006). Over the past decade, Asia has been the most frequently and significantly hit region occupying 80 % of the major natural disasters worldwide.

Less than 10 % of natural disaster losses in developing countries are insured as several markets imperfections have served to impede development of markets for transferring natural disaster risks. Adverse selection and moral hazard are inherent to any form of conventional insurance products when insured have total control of

S. Chantarat (✉)
Crawford School of Public Policy, The Australian National University, Canberra, Australia
e-mail: sommarat.chantarat@anu.edu.au

K. Pannangpetch
Faculty of Agriculture, Khon Kaen University, Khon Kaen, Thailand

N. Puttanapong
Faculty of Economics, Thammasat University, Bangkok, Thailand

P. Rakwatin
Geo-Informatics and Space Technology Development Agency, Ministry of Science and Technology, Bangkok, Thailand

T. Tanompongphandh
Faculty of Economics, Kasetsart University, Bangkok, Thailand

and private information on the indemnified probability. Transaction costs of financial contracts necessary for controlling these information asymmetries and for verifying claimed losses are extremely high relative to the insured value especially for smallholders. Limited spatial risk-pooling potential resulted from covariate nature of natural disaster losses further impedes the development of domestic insurance market, unless local insurers can transfer the risks to international markets.

Without effective insurance market, public disaster assistance and highly subsidised public insurance programs have been the key supports for affected population in developing countries. The increasing frequency and intensity of these covariate shocks, however, could jeopardise the adequacy, timeliness and sustainability of these programs (Cummins and Mahul 2009). These public programs are largely prone to moral hazard, which could easily alleviate the program costs through induced risk taking incentives or underinvestment in risk mitigating activities among vulnerable populations. Without proper targeting, these programs could further crowd out private insurance demand impeding the development of healthy domestic insurance market.

Households in developing countries, thus, are disproportionally affected by disasters due to larger exposures but limited access to effective risk management strategies. While literatures analyse the wide array of informal social arrangements and financial strategies that households employ to manage risk, in nearly all cases these mechanisms are highly imperfect especially with respect to covariate shocks and in many cases carry very high implicit insurance premiums. The resulting long-term impacts of catastrophic shocks on their economic development thus have been widely evidenced in the literatures (cf. Barrett et al. 2007 for a review).

This chapter explores the potentials of the increasingly used index-based risk transfer products (IBRTPs) in resolving the key market imperfections that impede the development and financing of sustainable natural disaster insurance programs in developing countries. Unlike conventional insurance that compensates individual losses, IBRTPs are financial instruments, e.g., insurance, insurance linked security, that make payments based on an underlying index that is transparently and objectively measured, available at low cost and not manipulable by contract parties, and more importantly highly correlated with exposures to be transferred. By design, IBRTPs thus can obviate asymmetric information and incentive problems that plague individual-loss based products, as the index and so the contractual payouts are exogenous to policyholders. Transaction costs are also much lower, since financial service providers will only need to acquire index data for pricing and calculating contractual payments. There will be no need for costly individual loss estimations. Properly securitising natural disaster risk into a well-defined, transparently and objectively measured index could further open up possibilities to transfer covariate risks to international reinsurance and financial markets at competitive rates.

As natural disaster losses are covariate, it would be possible to design IBRTPs based on a suitable aggregated index. These opportunities, however, come at the cost of basis risk resulting from imperfect correlation between an insured's actual loss and the behaviour of the underlying index on which the contractual payment is

based. IBRTPs will be effective only when basis risk is minimised. The contracts need to also be simple enough to hold informed demand among clients with limited literacy in developing countries, and to be scalable to larger geographical settings to ensure efficient market scale. Trade-offs among basis risk, simplicity and scalability thus constitute the key challenges in designing appropriate IBRTPs for developing countries.

Over the past decade, IBRTPs have emerged as potentially market viable approaches for managing natural disaster risk in developing countries. The growing interests among academics, and development communities have resulted in at least 36 projects in 21 countries worldwide covering risks of droughts, floods, hurricanes, typhoons and earthquakes based on objectively measured area-aggregated losses, weather and satellite imagery products.[1] Contracts have been designed to enhance risk management at various levels ranging from farmers and homeowners as target users to macro level, allowing governments and humanitarian organisations to transfer their budget exposures in provision of disaster relief programs to the international markets.

The consensus, however, has not been reached if and how IBRTPs could work in developing country settings for several reasons. First, current literature[2] tends to either lack rigorous analysis of basis risk and welfare impacts or use aggregated data to perform such analysis. Hence, less could be learnt ex ante about the value of the contracts to the targeted population. Second, contract designs to date are context specific, making it very difficult to be scaled up in other heterogeneous settings. Finally, as most of the current studies are small in scale, less has been explored on the potentials for portfolio risk diversifications, transfers and financing.

This chapter complements existing literatures, especially on the rigorous analysis and applications of IBRTPs in Asia. We provide an analytical framework and show empirically how to use a combination of disaggregated and spatiotemporal rich sets of household and disaster data, commonly available in developing countries, to design nationwide and scalable IBRTP contracts, to analyse hedging effectiveness and welfare impacts at a disaggregated level and to explore cost effective disaster risk-financing options. We explore the potentials for development of nationwide index insurance program for rice farmers in Thailand. We analyse contract design based on three forms of indices: (1) government collected provincial-averaged rice yield, (2) estimated area yield constructed from scientific

---

[1] Much literature has depicted opportunities and challenges of implementing IBRTPs. See IFAD and WFP (2010), Barnett et al. (2008), for example, for review. See Chantarat et al. (2007, 2008, 2011, 2013), Clarke et al. (2012) and Mahul and Skees (2007) for examples related to IBRTP designs in the developing world, and Mahul (2000) for examples related to agriculture in high-income countries.

[2] With the exception of some on-going new projects, see for example, Chantarat et al. (2013) and various piloted projects funded by USAID-I4 Index Insurance Innovation Initiative at http://i4.ucdavis.edu/projects/. These ongoing pilot projects undertake rigorous contract design and ex-ante evaluation using high-quality household welfare data in addition to their proposed ex-post evaluation through multi-year household-level impact assessment.

crop-climate modelling and (3) various constructed parametric weather variables. These indices differ in risk coverage, exposure to basis risk, level of simplicity and scalability. Disaggregated welfare dynamic data obtained from the multi-year repeated cross sectional household survey are then used to estimate basis risk and to evaluate the relative hedging effectiveness of these indices given the above trade-offs.

The nationwide design coupled with spatiotemporal rich indices data further allows us to explore portfolio risk diversification and transfers through reinsurance and securitisation of insurance-linked security in the form of catastrophe bond. And through simulations based on disaggregated nationwide household dynamic data, we finally explore potential impacts of the optimally designed index insurance program under various public–private integrated risk financing arrangements. Except for the existing literature on Mongolia (Mahul and Skees 2007) and India (Clarke et al. 2012), this chapter is among the very first to study IBRTPs using a countrywide analysis. Using commonly available data sets further enhance scalability of our analysis to other settings in the region.

The rest of the chapter is structured as following. Section 2 presents the main empirical results illustrating the potentials of IBRTPs for rice farmers in Thailand. Section 3 concludes with discussions on challenges and opportunities in implementing IBRTPs and implications of our studies for the rest of Asia.

2 Index-Based Disaster Insurance Program for Rice Farmers in Thailand

Rice is the country and region's most important food and cash crop. In Thailand, rice production occupies the majority of arable land with the largest proportion of farmers (18 % of the population) relying their livelihoods on. Improving and stabilising rice productivity is thus one of the core prerequisites for the country's economic development. Thai rice production, however, has been increasingly threatened by natural disasters, especially droughts and floods.

Thai farmers typically take out input loans and expect to pay back with income raised through the harvested crop. Production shocks thus usually bring about increasing level of accumulated debt, as farmers could face difficulties in repaying their loans and in smoothing their consumption. These translate directly to high default risk facing rural lenders, especially the Bank of Agriculture and Agricultural Cooperatives (BAAC) holding the majority of agricultural loan portfolios in the country. While instruments that allow rice farmers to hedge other key risks are largely available—e.g., public rice mortgage program for hedging price risk— sustainable insurance that could insure farmers' production risks without distorting their incentives to improve productivity are still largely absent.

2.1 Rice Production, Exposures to Natural Disasters and the Current Programs

There are about 9.1 million hectares of rice growing areas in Thailand in 2010.[3] Figure 9.1 presents variations in rice paddy areas and production systems across the country's 76 provinces.[4] The key growing provinces, where rice paddy occupies at least 50 % of the total arable areas, are clustered mainly in the central plain especially around Chao Phraya River basin and the lowland Northeast. Small numbers of rice growing provinces are also scattered around the upland North and the South.

Production regions vary in cropping patterns due to heterogeneous irrigation systems, ecology, soil and weather patterns. Irrigation is available in less than 25 % of the total growing areas. These occupy most of the central provinces and some areas in the North and the South, allowing farmers to cultivate two crops a year. Yields thus tend to be higher in these regions. The majority of rain-fed production occupies almost the entire key growing areas in the lowland Northeast, relies extensively on rainfall and so harvests lower yields. The main crop cycles typically start with the onset of annual rain, which usually comes during mid-May to November and varies slightly across regions. The second crop can then be grown throughout the rest of the year depending on water availability. As the key growing areas around Chao Phraya River basin are flood prone, crop cycles deviate slightly in order to avoid extended flood periods.

Rice cropping cycle spans about 120 days from seeding to harvesting (Siamwalla and Na Ranong 1980). Long dry spells and extended flood periods appear as the two key shocks affecting productions with increasing frequency. Sensitivity to these key disasters varies across different stages of crop growth. According to World Bank (2006)'s collective scientific findings,[5] the first 105-day period from seeding to grain filing critically requires enough water, and thus is vulnerable to long dry spells that could result from late or discontinued rain. Farmers are also already well adapted to small dry spells by adjusting their planting periods or re-planting when loss occurs early in the cycle. As cycle progresses to maturity and harvesting (during the 105–120 day period that typically fall into the peak of seasonal rain), plants become vulnerable to extended flood that could come about at least when 4-day cumulative rainfall exceeds 250 mm.

---

[3] Data are obtained from the Office of Agricultural Extension, Ministry of Agriculture and Cooperatives, Thailand. There is no significant trend from the annual areas since 1980.

[4] The number of provinces has just recently increased to 77 with one additional province added in the Northeast 2011. Our spatiotemporal data are extracted using the un-updated 76-province GIS information.

[5] These results are obtained from PASCO, Co.'s study using a combination of scientific literature reviews, agro-meteorological model (DSSAT) with detailed geographical information and ground checking with the local experts in the key-growing province, Phetchabun, and flood plain modelling.
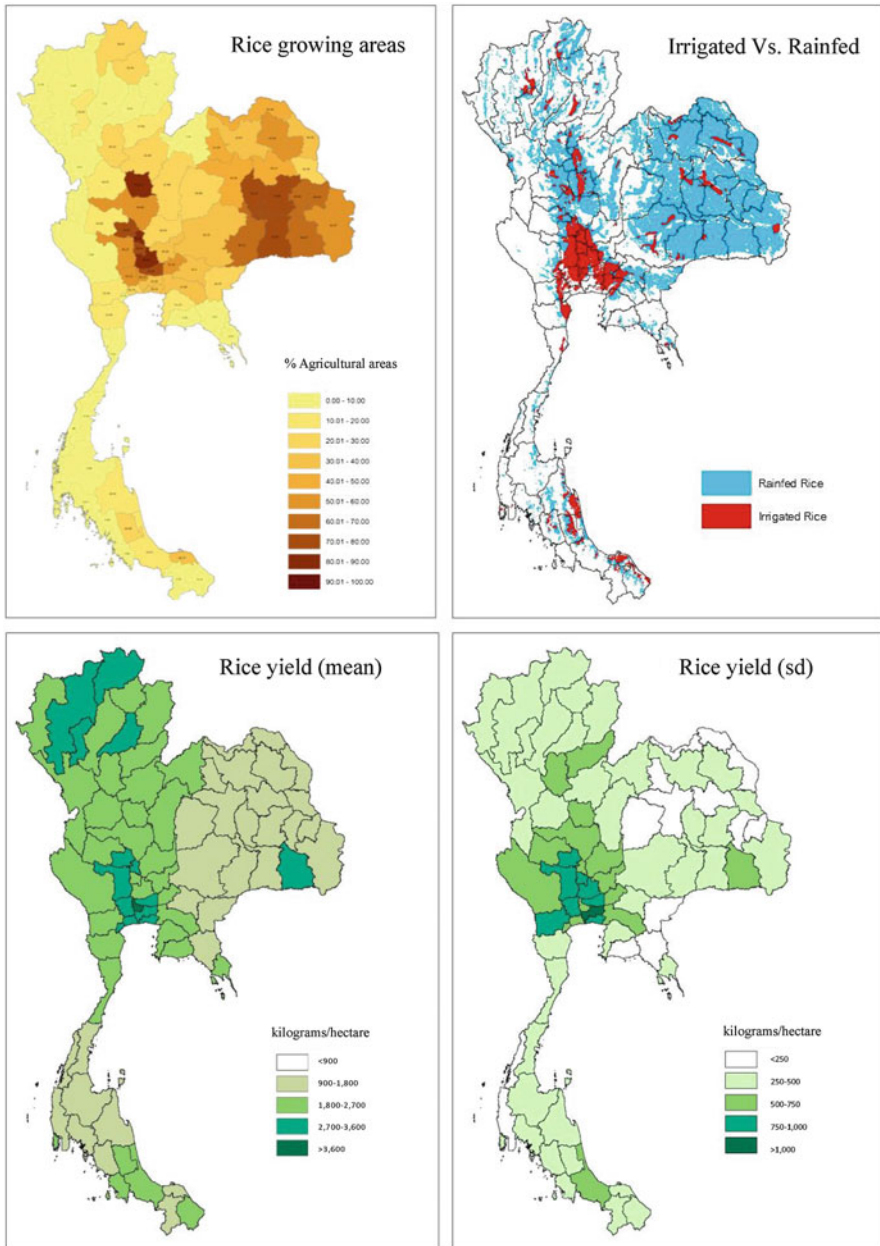
Fig. 9.1 Growing areas and variations in rice production in Thailand. *Note*: Data are obtained from GISTDA, Ministry of Science and Technology for the two top graphs and from Ministry of Agriculture and Cooperatives for the two bottom ones

Catastrophic crop losses from dry spells typically occur in the rain-fed areas during the onset of rain in July–August, whereas, losses from extended floods occur in the peak of rain during September–October. Exposures differ across regions. The north-eastern rain-fed production are especially vulnerable to long dry spell, while most of the irrigated production in the central plain are subject to long periods of deep flooding annually. Productions in the South are vulnerable to floods caused by thunderstorms (Siamwalla and Na Ranong 1980). Pest also serves as one of the key covariate risks for rice production. Figure 9.2 presents government records of incidences and spatial variations of actual rice crop losses from these three main shocks in 2005–2011. Flood losses occur with the highest frequency and significance relative to others.

Over the past decade, the Thai government has provided disaster relief program for farmers when disaster strikes. The program compensates about 30 % of total input costs for farmers, who live in the government declared disaster provinces and are verified by local authorities to experience total farm losses. Government spends about 3,350 million baht[6] on average per year for rice farmers affected by droughts, floods and pests. And the program cost could increase up to 40 % in some extreme years. Despite these tremendous spending, results from randomised farmer survey imply that the compensation is largely inadequate and subjected to serious delay especially from loss verification process (Thailand Fiscal Policy Office 2010). There are also increasing evidence of moral hazard associated with the program, especially as farmers start growing the third crop off suitable season.

The nationwide rice insurance program—a top-up program for disaster relief—was piloted in 2011. The program was underwritten by a consortium of local insurers and reinsured by Swiss Re (2011b). At 50 % subsidised premium rate of 375 baht/ha nationwide, the program covered main rice season, and compensated farmers up to 6,944 baht/ha (about 30 % of farmers' input costs) should they experience total farm losses from droughts, floods, strong winds, frosts and fires during the cropping cycle. About 1.5 % of growing areas were insured in 2011. The flood resulted in a loss ratio of as high as 500 % for the first year. Reinsurance prices thus inevitably increased more than double making it not market viable for the following years. This program continued in 2012 at the same (highly subsidised) rate but with government now taking the role as an insurer.

The current program thus resumes various inefficiencies and market problems, commonly evidenced in the traditional crop insurance to jeopardise the program's sustainability (Hazell et al. 1986). First, like other conventional insurance, the program would be subjected to moral hazard, e.g., when it induces additional risky off-season rice cropping, etc. Second, high direct subsidisations distorted market prices and thus could reduce sustainability of the market in the longer run. This could further exacerbate incentive problems. Third, this voluntary program is offered at one single premium rate for farmers with different risk profiles. It could

---

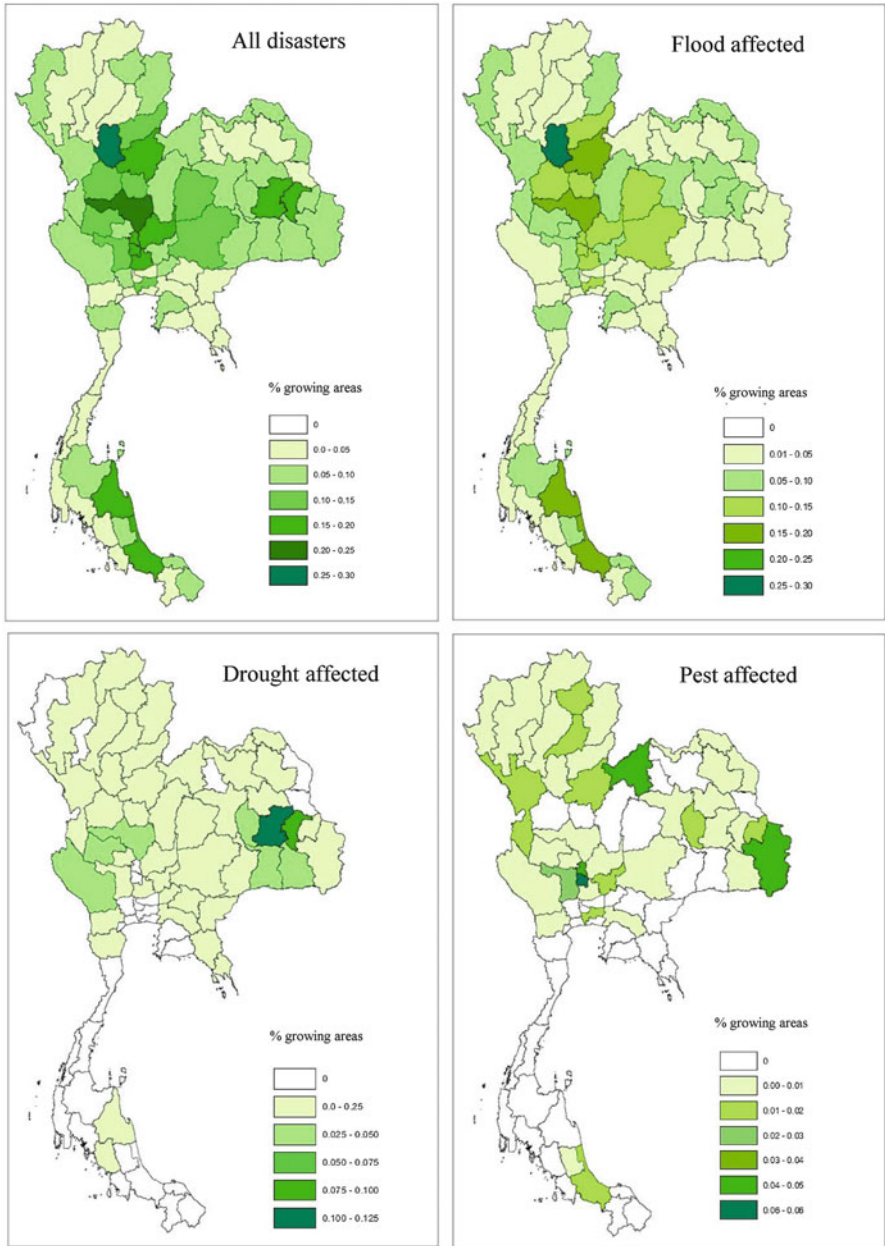[6] USD 1 = 31.81 baht (Bank of Thailand as of May 29, 2012).

Fig. 9.2 Rice growing areas affected by key disasters (2005–2011). *Note*: Data are obtained from Thailand Ministry of Agriculture and Cooperative

potentially signify adverse selection and moral hazard.[7] Fourth, because the government's declaration of disaster areas can be subjective in nature, asymmetric information at the government level could further arise. The highly subjective local verification of losses could potentially induce rent seeking at various levels, further affecting the commercial sustainability of this program. The highly subjective and non-transparent nature of loss measures would no doubt lead to increasing risk pricing in the international market. Finally, the program resumed inefficiencies in time and cost of loss verification in the relief program.

2.2 Data

We use five disaggregated nationwide datasets in this study. The first four sets are used to construct objectively measured indices for index insurance design, and the last set represents variations in households' incomes from rice production, and thus is used to establish optimal contract design, basis risk and hedging effectiveness associated with various designed contracts.

First, measures of area-yield indices are drawn from the provincial rice yield data collected annually by the Office of Agricultural Extension at Thailand Ministry of Agriculture and Cooperatives (MoAC). The data are available for all the provinces nationwide from 1981 to 2010 and were collated from a combination of an annual survey of randomised villages in each province and official records by local agricultural extension offices. They are thus representative at the provincial level. Yield data reflect total yield from all crops harvested each year. To remove time trends potentially resulting from technical change, improvements in varieties, irrigations and other management practices, we de-trend the data using a robust Iterative Reweighted Least Squares Huber M-Estimator[8] to first estimate the time trend.

Second, objective measures of weather indices are drawn from 20×20 km gridded daily rainfall data obtained from the simulated regional climate model ECHAM4-PRECISE constructed by Southeast Asia System for Analysis, Research and Training (START) as part of their regional climate change projections. These simulated climate data were verified and rescaled to match well with the comparable data from observed weather stations (Chinvanno 2011). These simulated weather data are available from 1980 to 2011.[9]

---

[7] Farmers in the risky areas would, in expectation, tend to be the majority of the purchasers of the cheaper contract relative to their risk profiles. And the heavily subsidised insurance contracts for those in the risky zones could further induce excessive risk taking behaviours.

[8] This trend estimation has been commonly used in agricultural time series especially when the underlying data are not normally distributed (Ramirez et al. 2003).

[9] These also include projected future climate data and are available at http://www.start.or.th/. The resolutions of these data could be improved. Attempts are current made in gridding weather data at lower resolutions.

Third, estimated rice yield data were then constructed using an integrated crop-climate model developed by Pannangpetch (2009). High resolution GIS maps of soil types (1999), rice growing areas constructed by LANDSAT 5TM (2001) and ECHAM4-PRECISE weather were first overlaid in order to cluster geographical areas into distinct simulation mapping unit (SMU)[10] representing the smallest homogenous areas, where crop response to weather conditions could be uniform. DSSAT crop model was then used to estimate longitudinal estimated rice yields driven by ECHAM4-PRECISE weather controlling for exogenous time-invariant SMU-specific GIS characteristics and crop management. These estimated yields reflect total yields from one (two) crops harvested in the rain-fed (irrigated) SMUs. As the simulated yield variations are driven solely by variations in weather, these data can serve as objectively measured index for IBRTPs.

Fourth, the remote sensing Normalised Difference Vegetation Index (NDVI)[11] data are extracted from Tera MODIS satellite platform every 16 days from 2000 to 2011 throughout the country at a 500-meter resolution. NDVI data provide indicators of the amount and vigour of vegetation, based on the observed level of photosynthetic activity (Tucker et al. 2005). This knowledge is critical in the construction of appropriate weather indices that ally well with different stages of crop growth. Some GIS information characterising production systems that could condition the sensitivity of rice production to shocks and records of annual crop cycles are also obtained from MoAC for cross checking with NDVI data.

Fifth, household-level incomes from rice production data are obtained from multi-year repeated cross-sectional Thai Socio-Economic Survey (SES) surveyed nationwide every 2–3 years from 1998, 2000, 2002, 2004, and 2006 to 2009 Thailand's National Statistical Office. Each round, a total of 34,000–36,000 households were randomly sampled from the sampled villages in all provinces (10–25 sampled households per village; 30–50 sampled villages per province). Because no household is sampled more than once during these surveys, our analysis thus can be based on repeated household cross sectional data. Subset of households from the six rounds, who reported their socioeconomic status as farm operator and rice farming as the main household enterprise, are used in this study. The subsample size in each round ranges from 2,500 to 3,100 households with households per province varying from 5 in the non-rice provinces to 150 in the key rice growing provinces. Because there is no direct measure of rice production, we use household's annual[12] income from crop production per hectare as a representation of y_{it}. This annual income measure thus includes income from more than one cropping seasons in irrigated areas. Other household and area characteristics are also extracted from SES data.

All of the GIS variables are first constructed at pixel level before downscaling to provincial level, so that these can all be merged with household-level data. Table 9.1

---

[10] This results in 9,254 SMUs covering all the 9.1 million hectares of rice growing areas nationwide. The size of constructed SMUs ranges from 0.16 to 35,900 ha.

[11] Data are available worldwide and cost free. See https://lpdaac.usgs.gov/content/view/full/6644.

[12] Farm incomes from the last month are also available, but the large variations in cropping patterns as well as survey timing constitute great difficulties in controlling for seasonality effects.

Table 9.1 Summary statistics of key variables

Variables		N	Mean	S.D.	Minimum	Maximum
Rice production and rainfall						
Rice growing areas, 1981–2010	– Country (million hectare)	30	9.2	0.2	8.7	9.5
	– Province (% total area)	2,240	53 %	24 %	2 %	92 %
Annual cumulative rainfall (cm), 1980–2011		2,432	425	124	179	889
Provincial yield (kg/ha/year), detrended 1981–2010		2,240	2,622	868	710	5,398
Rice farming households						
Household crop production income (baht/ha/year)		18,216	40,246	31,541	0	98,137
Rice cropping land size (hectare)		18,216	1.92	3.56	0.16	47.00
Number of times cultivated rice per year		18,216	1.64	1.13	1.00	3.00
Number of members working on farm		18,216	2.75	1.24	1.00	6.00
Input and operating cost per cropping season (proportion of income)		18,216	0.49	0.31	0.37	0.89
Household takes out loans for input cost each season = 1		18,216	0.89	0.23	0.00	1.00
Total outstanding agriculture loans (proportion of annual income)		18,216	1.41	6.94	0.00	256.25
Annual Interest rate on 12-month agricultural loan		18,216	0.06	0.03	0.02	0.15
Household size		18,216	3	1	1	6
Head age		18,216	50	14	17	94
Head female = 1		18,216	0.17	0.38	0.00	1.00
Head highest education—primary = 1		18,216	0.85	0.38	0.00	1.00
Head highest education—secondary = 1		18,216	0.05	0.20	0.00	1.00
Head highest education—university = 1		18,216	0.00	0.00	0.00	0.00
Head highest education—vocational = 1		18,216	0.00	0.06	0.00	1.00
Own house = 1		18,216	0.96	0.18	0.00	1.00
Own agricultural land = 1		18,216	0.81	0.42	0.00	1.00
Provincial production characteristics						
Households' farm located in the irrigated areas = 1		77	0.22	0.43	0.00	1.00
Upland areas (% total rice paddy)		77	6 %	27 %	0 %	100 %
Flood plain areas (% total rice paddy)		77	12 %	47 %	0 %	100 %
River basin areas (% total rice paddy)		77	19 %	41 %	0 %	100 %
Indices (% of provincial long-term mean)						
Provincial yield index, 1981–2010		2,240	100 %	14 %	41 %	146 %
Estimated yield index, 1980–2011		2,432	100 %	24 %	57 %	146 %
Cumulative rainfall index, 1980–2011		2,432	100 %	27 %	29 %	154 %
Moving dry spell index, 1980–2011		2,432	100 %	35 %	38 %	165 %
Moving excessive rain spell index, 1980–2011		2,432	100 %	31 %	41 %	179 %

provides summary statistics of the key variables extracted from these five data sets. Overall, mean de-trended provincial averaged rice yield stands at 2,622 kg/ha with high standard deviation capturing the variations across households and years. Household's averaged income from rice production is at 40,246 baht per hectare per year. This results from cultivating 1–3 crops (with 1.64 crops on average) a year. Total input costs are averaged as high as 49 % of income[13] implying that households earn about 20,525 baht as farm profit per hectare per year. Mean rice-growing areas per household is about 1.92 ha. About 89 % of households take out input loan each season. And critically, their accumulated agricultural debt stands at an average of 141 % of annual income in any given year. Apart from the lowland majority, 6 % of total rice growing areas are upland, 12 % is flood prone and 19 % locates near river basin.

2.3   Index Insurance Designs for Thai Rice Farmers

Various spatiotemporal data sets allow us to explore various standard index insurance contracts for Thai rice farmers based on the following constructed indices.

First, direct measures of area yields $\overline{y}_t$ can be constructed from annual provincial yield data. As it offers protection against any covariate risks affecting provincial yield, not just from weather, it could perform well in the case of Thai rice, where pest constitutes one of the key covariate threats. Second, estimated provincial yields $y(w_t)$ can be constructed from the SMU-specific modelled yields. To the extent that the complex crop-climate predictive model performs well in predicting weather-driven yield shocks, this index could provide good hedging effectiveness for farmers. Third, we explore various parametric weather indices w_t. But because the sensitivity of plants to weather shocks varies across stages of crop growth, knowledge of cropping cycles and how they vary spatially and temporally are thus critical.

2.4   Cropping Cycles and Weather Indices

Smoothing [14] the provincial NDVI data in a 1-year window results in uni- or bi-modal patterns. Each of these NDVI modes corresponds well with one full 120-day crop cycle. These smoothed provincial NDVI patterns can then be clustered into six distinct zones with homogenous crop cycles. Normal starts of the main and second crops in the irrigated areas vary across flood prone lower Central

---

[13] These statistics align well with findings in Isvilanonda (2009).

[14] Simple local polynomial smoothing is used over all the pixels that fall into provincial boundary over 2000–2011.

(mid May, December), upper Central and North (July, January) and South (August, March). Normal starts of the main crop in the rain-fed areas follow those of the irrigated zones with those of Northern Province sallying well with those of the North. The variations of crop cycles observed objectively from the patterns of NDVI also align well with the MoAC-collected records of cropping patterns in some key provinces.

These six distinct zone-specific crop cycles then form a basis for constructing provincial weather indices. For each crop cycle, we extend World Bank (2006)'s crop scientific findings and so explore two provincial dry spell indices covering weather conditions in the first 105 days and a flood index covering those in the 106–120 days of the cycle. These indices are constructed for both main and second crops in the two-crop zones opening a possibility that farmers can obtain insurance protection for both crops. All weather indices are constructed first at pixel level and then averaged toward provincial indices.

First, a simple cumulative rainfall index (CR) can be constructed from daily rainfall. The level of CR below some critical strikes thus could reflect the extent of dry spell that could in turn damage rice production. The key advantage of this is its simplicity. Hence this index has been used in various piloted projects including one in the north-eastern province in Thailand.[15] This simple index, however, might not reflect the extent of dry spell well, as it fails to take into account how rainfall is distributed within 105-day period. In particular, high CR could result from couple large daily rains and a long dry spell (that would otherwise damage crop).

Alternatively, a moving dry spell index (MD), which measures the extent that 10-day cumulative rainfall falls below the crop water requirement (30 mm for 10-day period) in each and every 10-day dry spell in the 105 cropping days, can be constructed. MD above some critical strikes thus could better reflect the extent of dry spell that really matters to rice production. This index has widely been identified to better quantify the extent of dry spells. But because of its relatively more complexity, this index has not been used widely.[16]

Continuous excessive rainfall is the key cause of extended flooding periods in the paddy fields. World Bank (2006) found that the 4-day cumulative rainfall above 250 mm can trigger high probability of extended flood causing losses to harvesting rice crops. We thus quantify flood index using a moving excessive rain spell index (ME) to measure the extent that 4-day cumulative rainfall excess 250 mm. But the extent that ME could determine extended flooding period and crop losses should also vary across production systems, which in turn determine soil type, drainage system, crop variety, etc.

The three weather indices so far are constructed based on the assumption that insured cropping cycles in each year and province follow the six smoothed zone-specific patterns. Because famers tend to adjust their production annually in order to

---

[15] Current contract piloted by JBIC and Sompo Japan insurance in Khon Kaen relies on simple cumulative rainfall are taken from July to September.

[16] For example, drought index insurance for maize piloted in Thailand since 2007.
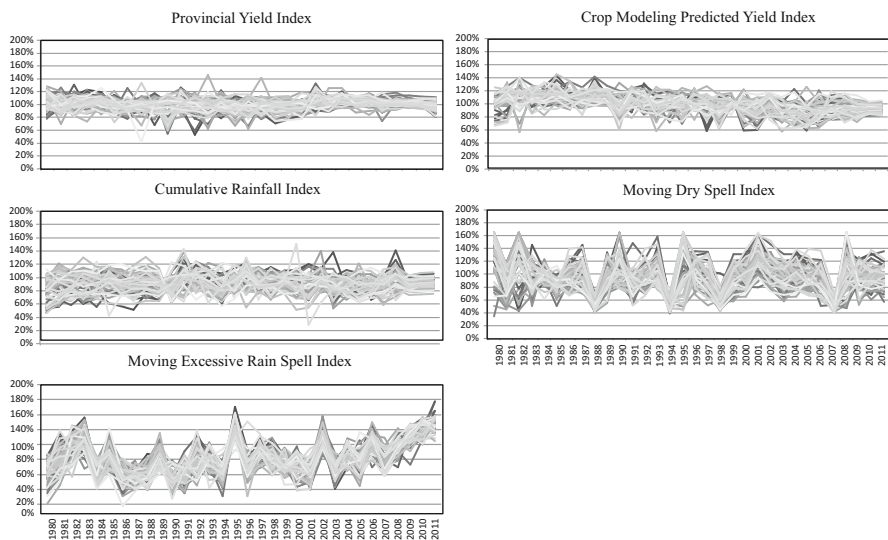
Fig. 9.3 Temporal and spatial distributions of the key indices

adapt to small inter-year variations in rainfall patterns, using fixed crop cycles as a basis for index construction might result in misrepresentations of crop losses from drought and flood events. Alternatively, indices can be constructed based on a dynamic crop cycle. Because successful seeding critically requires at least 25 mm of rainfall (World Bank 2006), the first day from the fixed zone-specific starting date when a 1-day, 2-day or 3-day cumulative rainfall exceeding 25 mm can be used to trigger the start of an insured cropping cycle, during when the underlying weather indices will be constructed. We experiment among the three choices above and choose the optimal threshold that yields the highest explanation power of the constructed indices in predicting actual losses.

In order to effectively compare contracts designed with various indices, we standardise these indices into relative percentage forms with respect to their provincial-specific expected value.[17] Table 9.1 provides statistics of these standardised indices. Figure 9.3 plots the five indices and their spatial distributions across all rice growing provinces.[18] Overall, provincial averaged, estimated yield indices and CR exhibit lower temporal variations relative to weather indices. Their spatial variations, however, are larger than the last two weather indices. MD seems

---

[17] Note that for $y(w_t), CR_t, MD_t, ME_t$, we standardise at the SMU and pixel first (using SMU and pixel specific moments) before aggregate them into provincial indices. This is different from taking average of index first then dividing by overall long-term average later. The latter case will result in index with lower variations since most the SMU-level variations are already smoothed out in the aggregation process.

[18] There are two values for each of the weather indices in the two-crop zones, one for each crop cycle.

to well capture the key covariate drought events in the country especially in 2008, 2001, 1995 and 1990. ME captures the key flood years well especially the catastrophic floods in 1995 and 2010–2011.

2.5   Basis Risks and Hedging Effectiveness

How well might these indices explain variations in household's annual crop income per hectare? Household data are merged with these indices at the provincial level in order to estimate (9.1). Without household panel, we instead use 6-year repeated cross sectional data to estimate, for each index, the following equation[19]

$$lny_{ilt} = X_{ilt}\gamma + D_l\mu + \eta_t + \lambda z_{lt} + \kappa D_l z_{lt} + \varepsilon_{ilt}. \tag{9.1}$$

The first three terms capture household's long-term expected income with X_{ilt} absorbing characteristics of households entered in each survey round, D_l absorbing provincial time invariant characteristics especially with respect to rice production systems (e.g., upland, flooded plain, closure to river basin) and η_t absorbing time effect that captures trend in income common across all households. The last three terms reflect stochastic shocks to household income. We also interact D_l with the index in order to capture variations in sensitivity of income to weather shocks across different production systems. This equation is estimated separately for irrigated and rain-fed regions using simple linear least squared with standard deviations clustered at provincial level.[20]

Different regressions explore how different indices can explain variations in farm income of the rice growing households controlling for household and provincial characteristics and time effects that determine household's long-term mean income. The first column shows that these controls explain about 40 % and 48 % of the income variations for households in the irrigated and rain-fed areas respectively, implying a maximum of 60 % and 52 % of income variations that households are still unable to manage using existing mechanisms. Except CR, all the indices significantly explain income variations though with different significant level. At 1 % significant level, the provincial yield index explains an extra 13 % and 11 % of income variations in the irrigated and rain-fed areas. The estimated yield perform relatively worse, explaining an extra 7 and 9 %.

Among weather indices constructed based on the fixed 6-zone crop cycles, CR performs the worst among all albeit its relative advantage in simplicity. While

---

[19] We reintroduce provincial subscript l here for clarification. The alternative approach of using pseudo provincial panel in estimating (1) controlling for provincial fixed effect would not take full advantage of these rich household data, as it would not yield household-level variations of basis risks.

[20] Ideally, we want to estimate provincial-specific β_l. The temporal observations per province are simply not enough with 6 years in Thai SES data.

explaining only 8 % of income in the irrigated areas, MD significantly explain up to 13 % of the income variations in the rain-fed areas, where cropping rely extensively on rainfall. ME explains only about 10 % of income variations in both areas. This raises question if it could serve as appropriate index for insuring flood losses in these areas. Combining MD and ME, we found that the two-peril index combination outperform others and explain 14 % and up to 19 % of income variations in irrigated and rain-fed areas respectively. Despite the added complexity, using dynamic crop cycles in determining index coverage does not add substantial improvement (if at all) to the explanation powers of the constructed weather indices.[21] Overall, the two-peril index combination MD + ME based on fixed zone-specific crop cycle thus strikes us as the potential basis risk-minimising underlying index for Thai rice contract.

How might hedging effectiveness of the optimal contracts based on these indices vary given the observed variations in household-level basis risks? The 6-year household data are limited in temporal variations, and so might under-represent the incidence of extreme events. Using the established relationship and distributions of household-level basis risk estimated in (16), we thus expand our data temporally and spatially by simulating 32-year income dynamics of representative households based on 32-year index data. In specific, for each year t from 1980 to 2011, 1,000 idiosyncratic shocks are randomly drawn for each province l from the province-specific empirical distributions $f(\varepsilon_{ilt})$ estimated using bootstrapping. Using the 32-year index data, provincial averaged household characteristics and provincial characteristics along with the estimated coefficients in (16), we then simulate 32-year income dynamics of 1,000 households in each province l from 1980 to 2011. Households' optimal coverage scales for various contracts and strike levels can then be estimated according to (7).[22] These then allow us to compute household-specific certainty equivalent values of consumption with and without various insurance contracts.

Figure 9.4 presents our results from 32-year income dynamics of 76,000 simulated households with assumed risk aversion $\theta = 3$ and actuarially fair contract prices. The two top panels compare averaged utility-based hedging effectiveness in term of increasing certainty equivalent values gained from obtaining insurance contract relative to no contract. The bottom two compare effectiveness based on simple variance reduction. Contracts are compared at the same level of payout frequency thus controlling for the same level of risk coverage and cost despite varying underlying risk distributions across indices and provinces.[23] Overall, both measures of hedging effectiveness of these actuarial fair priced contracts increase at

---

[21] Two-day cumulative rainfall exceeding 25 mm is chosen to trigger the start of each crop cycle, as it provides the best results comparing to others. This chosen trigger might not serve as an appropriate trigger for crop cycle just yet.

[22] As the estimated coefficients are specific at provincial level (not household), the simulated households' optimal coverage scales are specific at provincial level.

[23] And so we would expect that specific strike level for each payout frequency to be different across indices and provinces depending on their specific underlying distributions.
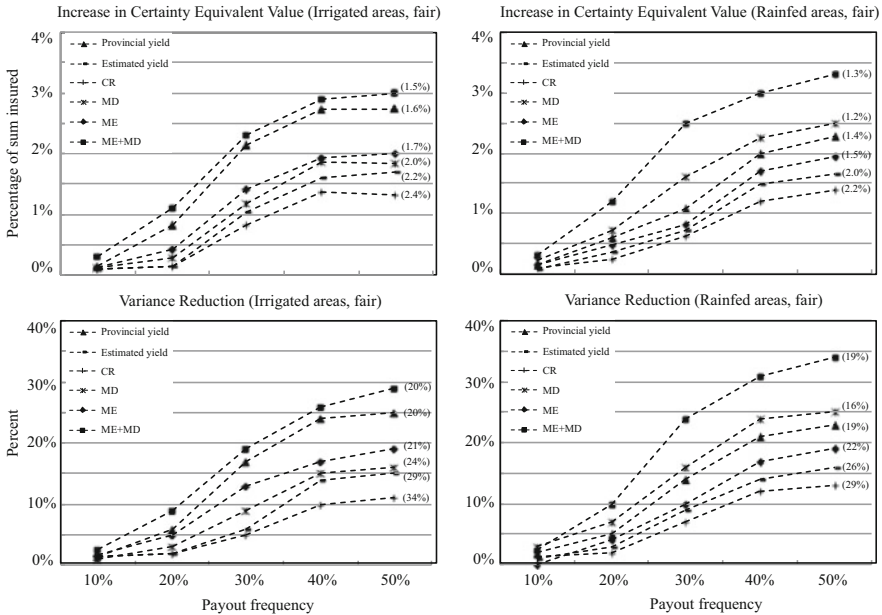
Fig. 9.4 Comparison of hedging effectiveness across optimal contracts. *Note*: Plots are averaged across 76,000 simulated households with CARA = 3. Average standard deviations around the estimated series in *parentheses*

a decreasing rate as payout frequency increases. Hedging effectiveness is very minimal for contracts with low payout frequency, e.g., of less than once every 5 years. This is due to the nature of systemic shocks on rice production, which tend to be less extreme but occur quite often. Variations of hedging effectiveness across households are high and vary across indices.

The optimal contracts with MD + ME index exhibit the highest hedging effectiveness in both measures. The provincial yield index, which was originally perceived to provide larger coverage for non-weather location systemic shock, performs almost as good as MD + ME in the irrigated zones but worse in the rainfed zones. The simplest contracts based on CR perform the worst in all cases. On average, the optimal MD + ME contracts covering 1-in-3 year losses could result in 2.3 % and 2.5 % increase in households' average certainty equivalent values in irrigated and rain-fed areas respectively. This could imply that the rates that households are willing to pay for the contracts on top of the fair rates. Up to 20 % and 25 % reduction in consumption variance in irrigated and rain-fed areas are possible, respectively. The MD + ME contract also appears with the lowest variations in contract performance across households. These results are also robust with respect to other underlying risk aversion and premium loading assumptions.

2.6   Optimal Contract Designs

The two-peril MD + ME contract is thus chosen as appropriate basis risk minimising contracts for Thai rice production in this study. For each cropping season, MD index is constructed for the first 105 days and ME index for the 105–120 days of the cycle. The fixed period of insurable crop cycle for each province is drawn from the zone-specific patterns. A seasonal contract payout per insured hectare is thus a combination of payouts from the two indices optimally scaled with α^*_{MD} and α^*_{ME} estimated using the risk profiles of 76,000 simulated households. The top panel of Table 9.2 reports mean provincial scales, actuarial fair premium rates and probable maximum losses by zones and strike levels for seasonal contracts available for the main crop.

Overall, the optimal coverage scales for the rain-fed zones are larger than those of irrigated zones due to their larger income sensitivities to these indices, especially the MD index. Actuarial fair rates are, however, larger at all strike levels for the irrigated zones, especially the irrigated flood prone lower central zone due to larger index variations. Mean provincial fair premium rates vary from 12–16 % for 1-in-2 year coverage to 6–9 % for 1-in-3 year coverage to 2–5 % for 1-in-5 year coverage. The variations of mean provincial premium rates across zones also imply spatial variations of the exposures to floods and droughts. The extent of catastrophic risks of the provincial contracts can be shown by estimated MPLs at $VaR_{99\%}$. The PMLs range from as high as 68 % of total sum insured for 1-in-2 year coverage to 56 % for 1-in-3 year coverage.

2.7   Portfolio Pricing and Potentials for Risk Diversifications

Making the seasonal contracts available for both main and second crops in the irrigated areas could further allow for temporal risk pooling across seasons within a year. The bottom panel of Table 9.2 reflects these results. While the optimal coverage choices remain the same (as they are established from an annual model (16)), the fair rates and PMLs reduce slightly for the seasonal contracts available for both crops in the three 2-crop zones. A nationwide portfolio of provincial contracts is then constructed with provincial weights established from combining provincial optimal scales and provincial share of rice growing area. The bottom row in each panel of Table 9.2 reflects the spatial risk pooling benefits. Catastrophic layers of the insurable risk of the nationwide portfolio reduce for all strikes relative to those of the individual provincial contracts.

How might the annual portfolio payouts co-move with annual returns of various tradeable goods in capital, commodity, future and weather markets? We found no significant pair-wise relationship between the portfolio of Thai rice insurance and the key market indices, e.g., Thai Stock Index (SET), NASDAQ, and securities in commodity or future markets. Our key results are the significant and negative

Table 9.2 Optimal seasonal contracts and actuarial fair rates

Zone	Strike = 110 % (Avg. payout freq. = 50 %)				Strike = 120 % (Avg. payout freq. = 30 %)				Strike = 130 % (Avg. payout freq. = 20 %)			
	α*(MD)	α*(ME)	Fair rate	PML	α*(MD)	α*(ME)	Fair rate	PML	α*(MD)	α*(ME)	Fair rate	PML
Contracts available for main crop only												
Irrigated Lower Central	0.7	0.8	16 %	68 %	0.8	0.9	9 %	56 %	0.8	0.9	5 %	38 %
Irrigated Upper Central-North	0.6	0.8	16 %	65 %	0.7	0.8	8 %	52 %	0.7	0.8	4 %	35 %
Irrigated South	0.8	0.9	14 %	59 %	0.8	1.0	7 %	49 %	0.8	1.0	3 %	32 %
Rainfed Lower Central	1.1	0.9	15 %	57 %	1.1	0.9	7 %	46 %	1.1	0.9	3 %	27 %
Rainfed Northeast-North	1.1	0.9	12 %	48 %	1.1	0.9	6 %	37 %	1.1	0.9	2 %	23 %
Rainfed South	1.0	1.0	12 %	46 %	1.0	1.0	6 %	32 %	1.0	1.0	2 %	19 %
Nationwide	0.9	0.9	14 %	59 %	1.0	1.0	7 %	47 %	1.0	1.0	3 %	29 %
Contracts available for both main and second crops												
Irrigated Lower Central	0.7	0.8	15 %	64 %	0.8	0.9	8 %	53 %	0.8	0.9	4 %	33 %
Irrigated Upper Central-North	0.6	0.8	14 %	59 %	0.7	0.8	7 %	48 %	0.7	0.8	3 %	31 %
Irrigated South	0.8	0.9	12 %	57 %	0.8	1.0	5 %	48 %	0.8	1.0	2 %	28 %
Rainfed Lower Central	1.1	0.9	14 %	57 %	1.1	0.9	7 %	46 %	1.1	0.9	3 %	27 %
Rainfed Northeast-North	1.1	0.9	12 %	48 %	1.1	0.9	6 %	37 %	1.1	0.9	2 %	23 %
Rainfed South	1.0	1.0	12 %	46 %	1.0	1.0	6 %	32 %	1.0	1.0	2 %	19 %
Nationwide	0.9	0.9	12 %	55 %	1.0	1.0	6 %	43 %	1.0	1.0	2 %	27 %

Note: Payout frequencies are for both perils from MD + ME. Optimal scales are for both contracts. Optimal scales, fair rates are averaged across provincial rates. PMLs are maximum provincial values. Prices are based on 1980–2011 historical burn rates. Price estimates from Monte Carlo simulations are comparable so omitted. The nationwide scales is averaged provincial scales weighted by shares of growing areas

Table 9.3 CAT bond linked with stop-loss reinsurance

	Capped (%)	100 % Stop-loss reinsurance on nationwide portfolio		
Required return	Principle losses	110 %	120 %	130 %
4 %	100 %	0.8412	0.8729	0.8898
	50 %	0.8823	0.8942	0.9064
6 %	100 %	0.8276	0.8511	0.8688
	50 %	0.8667	0.8818	0.8997
10 %	100 %	0.8096	0.8212	0.8389
	50 %	0.8532	0.8734	0.8935

Note: Bond prices are calculated assuming market rates of stop-loss reinsurance = fair rates + 3 % PML

relationships between the portfolio and various actively traded weather indices from around the world. While these results are based on low frequency (aggregated annually) data, they could signal potential diversifying values of Thai rice insurance portfolio in the portfolio of global weather risks.

2.8 Risk Financing and Transfer

The net payout position of risk aggregators, e.g., local insurers, appears with great exposures especially during the key catastrophic years. For example, the occurrence of both catastrophic drought and flood in 1995 result in net payouts of as high as 43 % of total sum insured for contracts with 1-in-3 year coverage (120 % strike). This signals the importance of international market risk transfers in ensuring the sustainability of the program.

Because the underlying risks are not as catastrophic as that of earthquakes, etc., with reasonable PMLs of about 49 % sum insured, we assume an optimistic case, where the potential market rates for these reinsurance contracts are established with an additional catastrophic load at 3 % of the estimated PMLs. This could reflect the potential costs of capital for reinsurer in holding necessary reserve or obtaining other risk financing instruments. At these potential market rates, we can illustrate some designs of a zero-coupon cat bond with principle payments linked with 100 % stop-loss reinsurance contracts for the nationwide portfolios.

Table 9.3 reports cat bond prices for various specifications of required rate of returns for investor, a cap (% of principle) that limit investor's principle loss if reinsurance contract triggers payouts and strike levels of nation wide insurance portfolio for the linked 100 % stop-loss reinsurance contracts. Cat bond with 100 % cap is thus riskier comparing to that with 50 % cap since an investor would be exposed to losing all of his/her principle should the catastrophic events triggered reinsurance payout. The required rates of return are set at 4, 6 and 10 % translating into risk premiums between 2.93 and 8.93 % at the current LIBOR rate

of about 1.07 %.[24] Comparing with other existing cat bonds (with relatively more catastrophic underlying risks) and the Mexican cat bond with as low as 2.35 % premium above LIBOR, it seems this chosen range of risk premiums is sufficiently representative of spreads required by investors in the market (Froot 1999). We note that the total return realised by investors when the bond is not triggered is always higher than the required return used in computing bond prices. The difference between the two presents the added premium associated with the catastrophic risk.[25] The bond prices thus decrease (hence the bond yields increase) with riskiness of the underlying reinsurance contract, the cap value and the required rates of return.

These results are, however, only for illustration of how Thailand's nationwide rice insurance portfolio might be securitised and transferred to international capital market. The actual potential of cat bond will also rely on the costs associated with securitising the contract relative to other means. The key feature that deviates this cat bond from others is its coverage of less extreme shocks relative to other earthquake- or hurricane-linked products in the market.

2.9 How Might This Nationwide Rice Index Insurance Program Work?

Our results so far imply that (1) the basis risk minimising contract with two-peril MD + ME index could provide up to 35 % reduction in the insured's consumption variance, (2) households are willing to pay between 2 and 4 % of total sum insured on top of the fair rates for contracts with 1-in-2 year to 1-in-3 year payout frequency, (3) it could be cost effective to price provincial seasonal contracts as part of a pooled nationwide portfolio and (4) opportunities could exist in transferring portfolio risks to international markets through some forms of illustrated reinsurance and securitisation. We now illustrate the potential market rates, how the designed program and public support can be integrated in the risk financing in order to enhance market viability, and more importantly, how the program could benefit farmers, agricultural lenders and government.

Table 9.4 reports potential market rates for the provincial contracts priced as part of the nationwide portfolio under various market arrangements. With a working assumption that the additive catastrophic load for a contract equals to the market

---

[24] LIBOR rate as of May 30, 2012 from www.global-rate.com.

[25] For example, an investor who purchased a cat bond with required return of 4 %, 50 % cap with 110 % strike at the price = USD0.8823 and received USD1 principle back 1 year later when reinsurance is not triggered, would realise a total compounded return of 12.4 %. The rate can be interpreted as including a risk free LIBOR rate of 1.07 %, 2.93 % premium associated with bond default and other risks not associated with the insured reinsurance risk, and an additional 8.4 % premium associated with this catastrophic risk associated with the reinsurance.

Table 9.4 Potential market pricings and arrangements for nationwide index insurance

		Market Arrangements							
		Potential market rates		With Public Financing of Tailed Risk beyond Capped Payout at					
				20 %		30 %		40 %	
Strike	Payout freq.	Mean	SD	Mean	SD	Mean	SD	Mean	SD
110 %	50 %	17.8 %	(4.6 %)	11.9 %	(3.1 %)	14.3 %	(3.3 %)	16.9 %	(3.7 %)
120 %	30 %	8.8 %	(3.7 %)	**4.2 %**	**(2.3 %)**	**6.4 %**	**(3.1 %)**	8.8 %	(3.7 %)
130 %	20 %	**3.1 %**	**(2.1 %)**	3.1 %	(2.1 %)	3.1 %	(2.1 %)	**3.1 %**	**(2.1 %)**
Increase in certainty equivalent value, CE^{insured}-CE^{uninsured} (% sum insured per season)									
Low risk aversion (θ = 1)		0.1 %		3.6 %		1.4 %		0.1 %	
Med. risk aversion (θ = 3)		0.2 %		4.2 %		2.0 %		0.2 %	
High risk aversion (θ = 5)		0.4 %		4.9 %		2.7 %		0.4 %	
Simulated impacts of insurance on households, agricultural loans and government (θ=3)									
Net income for consumption (No I = 25,314 baht/year)		24,275 (28,978)		33,052 (24,464)		31,278 (26,464)		24,275 (28,978)	
5-years loan outstanding (No I = 90 % 1-year income)		39 % (57 %)		0 % (0 %)		9 % (17 %)		39 % (57 %)	
Input loan default rate (No I = 47 % per year)		21 % (12 %)		0 % (0 %)		8 % (4 %)		21 % (12 %)	
Government spending (No I = 0 million baht)		0 (0)		843 (3,249)		297 (1,580)		0 (0)	

Note: The potential market rates = fair rates + market rates = fair rates + 3 % PML. Payouts are capped as % of total sum insured. Those in *bold* are welfare maximising contract strike for each market arrangement. CE and impacts of insurance are for the welfare maximising coverage. Results vary across provinces. Mean reported with standard deviations in parentheses

rate for 100 % stop-loss reinsurance coverage for that contract, our pricing results in an additional 50 % mark up from the fair rates.[26] As catastrophic loads drive high mark-up rates, insurable risk can then be layered so that complementary public financing of tailed risk beyond some capped indemnity payouts from insurers could result in reduction of market rates. As shown in Table 9.4, when insurer's payouts are capped at 30 % of total sum insured, market rates for the 1-in-2 year and 1-in-3 year contracts reduce dramatically to their fair rates (and even below their fair rates for a cap of 20 %).[27]

We now base an analysis on 32-year income dynamics of 76,000 simulated households with welfare maximising contract strike level under each market arrangement. The associated increases in certainty equivalent consumption are also reported for farmers with low, medium and high levels of risk aversion. The 1-in-5 year contract appears optimal under fully market-based index insurance program. But with low risk coverage, its utility-based hedging effectiveness is low but still positive, implying that on average households are willing to buy this contract at the market rate and contribute up to 0.4 % of total sum insured on top of the current rate. With government financing indemnity payouts beyond 20–30 % caps, the welfare maximising strike shifts to 1-in-3 year contract. These market arrangements also result in larger hedging effectiveness through lower insurance prices and larger resulting optimal risk coverage.

Which market arrangement is appropriate for this nationwide index insurance program? We explore this further by simulating the potential impacts on farmers, agricultural loan portfolios and government of these market arrangements for the nationwide index insurance program, as well as the existing program. To do so, several assumptions are made. First, we assume that all 76,000 simulated farmers are clienteles of BAAC. Each year, they take out a loan to finance total input cost and to obtain insurance coverage for income from all cultivated rice crops (one or two). Total production income is then used to pay back the loan. From SES data, total input cost is assumed to be 49 % of averaged provincial crop production income, which also vary across provinces. Household is assumed to pay back their loan as much as is feasible—the maximum repayment is reached when net income available for consumption drop to zero.

With these assumptions, household's production income available for consumption per hectare per year thus reflects total income after receiving insurance payout

---

[26] This mark up is comparable to other existing index insurance programs in other part of the world. These market rates are comparable to other pilot projects for rice insurance in Thailand. For example, 4.64 % rate changed for recently piloted deficit rainfall index insurance covering only drought peril for only the main rice production in Khon Kaen province during July–September.

[27] Because the extreme layers of risk are not so catastrophic, capping at higher level beyond 40 % of sum insured will result in more or less the same effects to market premium rates. The market premium rates for 130 % strike contract do not change with payout caps, as the contracts' maximum payout rates are already well below the caps.
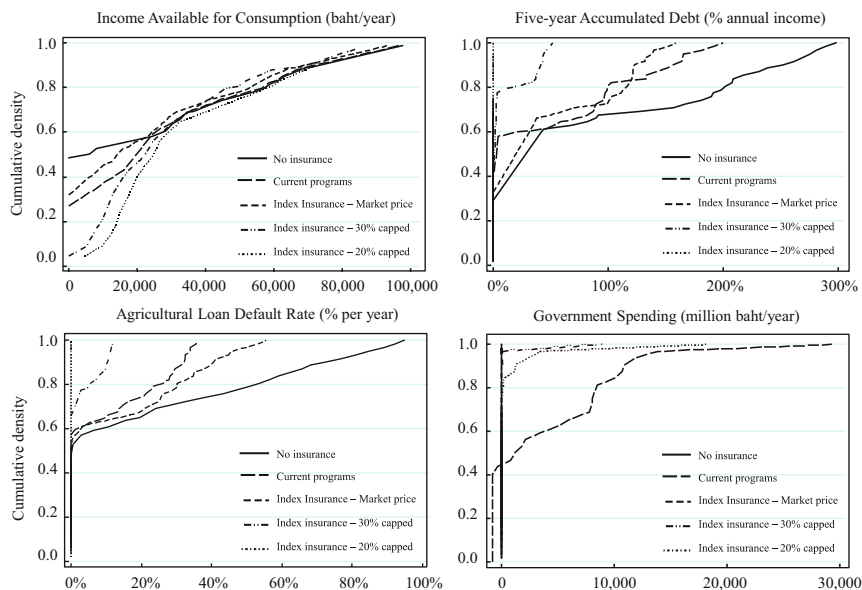
Fig. 9.5 Simulated impacts of various nationwide index insurance arrangements. *Note*: Cumulative densities based on 32-year dynamic data of 76,000 simulated households in 76 provinces nationwide

and netting out all the accumulated loans outstanding up to that year: The nominal interest rate r is at 6.75 % per year. From SES data, we assume that household cultivates 1.92 ha of rice paddy each year.

Based on 32-year dynamic data of 76,000 simulated households, Fig. 9.5 plots cumulative densities of income available for household consumption, 5-year accumulated debt position realised at any given year, BAAC's annual loan default rates and annual government spending[28] under various schemes. The bottom panel of Table 9.4 also reports means and SDs of these impacts. With no disaster insurance market and government support, there is about 50 % probabilities that income available for consumption of Thai rice farming households could collapse to zero. Household's 5-year accumulated debt realised in any given year is almost always positive with an average of 90 % of annual production income. This outstanding debt could be as high as 300 % of average annual income in any given year. And BAAC's loan default rate is estimated at 47 % per year on average. The existing program with a combination of government's disaster relief and subsidised

---

[28] We rescale the simulated representative sample to represent the current 9.2 ha of growing areas nationwide. The current sample represents 63 similar households (9,200,000/(76,000 × 1.92)).

insurance[29] results in favourable distributional impacts that almost always first order stochastically dominate those of the baseline. The key drawback, however, is the tremendous government budget exposure, which stands at an average of 8,890 million baht per year, and could reach 29,930 million baht in some key years.

The market driven index insurance program without government support could also result in dramatically improvement in distributional impacts relative to the baseline case of no market and government support. The probabilities of zero income available for consumption, the averaged long-term debt accumulation and BAAC's loan default rates reduce by half and also with great reduction in variations. These distributional impacts are, however, relatively smaller on average but not necessarily first order stochastically dominated by those of the existing program. This is because, on the one hand, farmers pay higher market prices for market-based index insurance product that covers smaller sets of disasters relative to the existing product. On the other hand, compensations from index insurance (based on provincial averaged income) tend to be larger than those of the existing program (based on 30 % of input cost) when the contract is triggered. With comparable impacts but no cost to the government, this purely market driven index insurance product could be appealing as one of the risk management tools for Thai rice farmers.

These distributional impacts further improve substantially for the index insurance program with integrated public financing of tailed risk beyond insurer's payout caps. At 30 % (20 %) payout cap, the resulting lower insurance prices and larger optimal risk coverage lead to more than 80 % (almost 100 %) reduction in probabilities of zero income available for consumption, long-term accumulated debt and BAAC's loan default rates relative to the baseline. The required public financing of these tailed risks are also substantially smaller in means and variations comparing to those required in the existing program. A case for public financing of tailed risk for Thailand's nationwide index insurance program thus could be strong. First, these public–private market arrangements are no doubt superior in both potential impacts on households and BAAC loan and on government's budget exposure relative to the existing program. And second, their distributional impacts are substantially larger than those under purely market-driven program.

---

[29] Without actual payout statistics, we assume that under the existing program, if household's actual crop income falls below its 1-in-3 year trigger level, they will be paid 3,787 baht per hectare (606 bath/rai) under disaster relief program and an extra 6,944 baht per hectare (1,111 baht/rai) if they pay for disaster insurance coverage at a subsidised price of 375 baht per hectare (60 baht/rai). We believe this assumption is reasonable, as (1) the program covers larger sets of disasters and (2) it makes payout conditional on government's declaration of disasters at very local levels with required actual loss verification. Because government disaster insurance is offered at highly subsidised price, our welfare optimisation implies that all representative risk-averse households will purchase full coverage. Hence 100 % insurance penetration rate is used. Note that we abstract from all the incentive problems associated with existing program that could result in larger exposure on government spending.

3 Conclusions and Implications for the Rest of Asia

This chapter laid out why index based risk transfer products could be attractive as a means to address important insurance market imperfections that have precluded the emergence and sustainability of formal insurance markets in developing countries. It then illustrated how disaggregated and spatiotemporal rich sets of household and disaster data, commonly available in developing countries, could be used to design and analyse nationwide, scalable disaster index insurance program for rice farmers in Thailand.

Relative to the direct measures of provincial yield and the estimated yield based on climate-crop modelling, we found that objectively measured weather data could be carefully constructed as basis risk minimising indices for index insurance contract. Objectively measured remote sensing data also proved to be useful in controlling for heterogeneous cropping patterns across larger geographical areas nationwide. The transparency of these weather indices and control measures along with their spatiotemporal availability could hold further advantages in scaling up contract designs to wider settings.

Using household level data in estimating basis risk and so in simulating contracts' hedging effectiveness, we found the resulting contract performance, optimal contract scales and pricings to vary largely across provinces and households. Contract designed at the provincial level—the most micro level given our representative data—was thus considered. Overall, the optimal provincial contract based on basis risk minimising combination of moving dry spell and moving excessive rain spell indices could result in up to 25 % reduction in the variations of household's income available for consumption. Simple cumulative rainfall, widely used in marketable contracts worldwide, however, appeared with the lowest performance. This raised concerns on the extent of basis risk associated with currently available contracts.

We found evidence of temporal and spatial diversification benefits, as we scaled insurance portfolio to cover all provinces nationwide and to cover the second crop grown among farmers in the irrigated areas each year. Thus return to scale in term of cost effective portfolio pricing can thus be achieved as part of nationwide, multi-seasonal coverage insurance program. Our finds could imply, on the one hand, that local risk aggregators could diversify their portfolio risk with appropriate hedging portfolio of global weather indices. On the other hand, tradable security linked with Thai nationwide insurance portfolio, e.g., cat bond, could be appealing in the international market as diversifiable security in various diversifying global portfolios.

The transparency of these weather indices and control measures in fact could further promote the possibility of cost effective risk transfers in the international market. We thus designed the corresponding reinsurance contracts and cat bonds, and illustrated their potentials and how these might be useful as risk transfer instruments. The key distinction of our cat bonds from others is the coverage of relatively higher frequency but lower impact losses from floods and droughts, comparing to other earthquake- or hurricane-linked products (cf. Skees et al. 2008).

Bringing all the results together, we asked what might appropriate market arrangement be to ensure sustainable implementation of this nationwide insurance program? Using disaggregated spatiotemporal rich data, we simulated the potential impacts on household welfare, agricultural loan portfolio and government of this nationwide program under various market arrangements relative to the current program. The purely market driven program was found to result in more than 50 % reductions in probabilities that household consumption collapsing to zero, in means and variations of 5-year accumulated debt and BAAC's annual loan default rates. As these impacts are comparable to those of the current program, albeit no budget exposure to the government, the market-driven program thus already proved as one of the effective disaster risk management tools for the setting. Properly layering insurable nationwide risk, we further found public financing of tailed risk beyond the 20–30 % capped to insurer's payout rates to result in substantial reduction in market premium rates. These in turn resulted in up to twice the impacts of the purely market-driven program, though with substantial smaller budget exposures to the government relative to the current government program. There could thus be a strong case for public financing of tailed risk in enhancing development values and market viability of Thailand's nationwide index insurance program.

How might this nationwide insurance program be implemented? An insurance indemnity pool of the nationwide index insurance contract could be created to allow local insurers to diversify their risks and contribute capital to the reserve pool, from where indemnity payments can be drawn. Reinsurance could potentially be acquired when indemnity payments exceed the pool but for the risk up to some appropriate capped level. Government could then finance the low frequency but catastrophic tailed risk through various options, e.g., offering complementary disaster insurance coverage for this tailed risk, providing the insurers direct coverage or financing of the transfers of this tailed risk.

The design and market arrangement of this nationwide index insurance for Thai rice farmers thus deviate largely from the current program. First, unlike direct premium subsidisation, public financing of the tailed risk does not distort market prices. The capped commercialized contracts are still sold at their market rates and the rates differ across provinces with different risk profiles. This prevents the potential adverse selection problem, likely to occur under the current scheme with one price for all. Second, the public financing of the tailed risk provides complementary, rather than substituting, coverage. This would not crowd out private demand for insurance, especially for the risk layer that should appropriately be absorbed by the households and market. Third, the government's budget exposure to financing of the tailed risk could be insured through some forms of IBRTPs. This, in turn, could enhance sustainability of the program. And more importantly, the key advantages of these index insurance design relative to the current loss-based insurance program are (1) relatively lower transaction cost, especially in loss verifications, (2) relatively lower adverse selection and moral hazard, (3) the contract still preserves insured household's incentive to take good care of their farms and so to adjust their cropping patterns to avoid risk since the indemnity is

regardless of their actions and (4) contract could potentially make timely payout as verification of these indices are in near real time.

Various limitations of the current study are worth noting with the goal to stimulate future required research ideas. First, our analyses are based on simulated rainfall data, not the actual data observed at various stations. Despite its relative advantage in the relatively richer spatial distribution, simulated data need to be verified with actual weather experienced at the micro level. Efforts are also underway in many developing countries, including Thailand, in constructing appropriate gridded data from observed station data in order to improve spatial distribution of the station data. Second, the current analysis mapped the relatively higher spatial resolution weather data with household data at provincial level, due to the lack of sub-district locators in the SES data. Efforts should be made in matching weather or disaster variables at the most micro level possible. Third, various spatiotemporal available remote sensing products, could have high potential in improving the measures and performance of the underlying indices. Efforts are underway in using these products to detect inter and intra year variations of rice growing areas, stage of crop growth, paddy losses and the extent of natural disasters (see Rakwatin et al. 2012, for example). And fourth, the observed increases in frequency and intensity of natural disasters imply the need for incorporating simulated impacts of climate change in the modelling and pricing of insurable risks.

The analytical framework as well as the empirical methodology proposed in this chapter should be replicable in other settings and in other developing Asian countries, where exposures to covariate natural disaster risks remain uninsured. The data sets used in this chapter should well be available in other Asian countries. The extended time series of spatiotemporal rich weather data as well as remotely sensed data are available worldwide at high quality and low cost.[30] And the high quality, national representative household dynamic welfare data similar to Thai SES data should well be available in the key Asian countries. Some examples include repeated cross-sectional household data from Indonesia National Socioeconomic Survey (SUSENAS), available every year from 1990 to 2010, from Vietnam Household Living Standards Survey (VHLSS), available every 2 years from 2002 to 2010.

This chapter offers an optimistic view of the potentially optimal designs, market viability and impacts of IBRTPs designed at a large nationwide scale. These results could deviate largely from actual implementation in the real world. At least, four key implementation challenges are worth noting. First, it could be difficult to establish informed effective demand among clientele with relatively low financial literacy in developing countries. Second, the presence of large basis risk could still

---

[30] Gridded weather data from WMO stations across Asia are available online at NOAA Global Daily Climatology Network (daily, 1900–present). Various satellite imagery Normalised Difference Vegetation Index (NDVI) available from NASA MODIS at 250 m resolution (15-day; 2000–present) and from NOAA AVHRR at 8 km resolution (10-day; 1982–2000). RADARSAT-1 and RADARDAT-2 with cloud-penetrating SAR sensor at 25 m resolution (every 15 day, 1995–present) have been increasingly used for flood monitoring.

be possible in some coverage areas. Third, cost of marketing and delivery mechanisms of the contract could still be high in developing countries. And fourth, the targeted clientele could have financial constraints in paying insurance premium.

These key challenges thus place significant implications on how index insurance program should be implemented in developing country settings. Should the insurance contracts be offered as a stand-alone or linked with other financial products? Linking with other existing financial products might resolve high implementation costs and relax some financial constraints among targeted clientele. Should the program be established at the micro, meso or macro levels? Extended investment in education, training and extension tools are thus critical if contracts are sold directly to households. At the meso level, rural banks like BAAC could obtain insurance contract to insure their loan portfolio, so that they can then lend insured loans to households. Groups and cooperatives can obtain coverage for their group saving or credit schemes. One testable assumption is that group-sharing network could potentially smooth out individual basis risk associated with index insurance contracts. Necessary randomised impact evaluation research has been launched around the world in attempt to address these questions. Extended discussion of key implementation challenges of IBRTPs in developing countries to data are summarised in Miranda et al. (2012) and IFAD and WFP (2010). Overall, the challenges are significant, but the considerable prospective gains associated with IBRTPs for enhancing development of sustainable disaster insurance programs in developing countries would seem to justify considerable new effort in this area.

References

Barnett, B. J., Barrett, C. B., & Skees, J. R. (2008). Poverty traps and index-based risk transfer products. *World Development, 36*(10), 1766–1785.

Barrett, C. B., Barnett, B. J., Carter, M. R., Chantarat, S., Hansen, J. W., Mude, A. G., et al. (2007). *Poverty traps and climate risk: Limitations and opportunities of index-based risk financing* (IRI Technical report 07-02). IRI, New York: Columbia University.

Chantarat, S., Barrett, C. B., Janvilisri, T., Mudsri, S., Niratisayakul, C., & Poonswad, P. (2011). Index insurance for pro-poor conservation of Hornbills in Thailand. *Proceedings of the National Academy of Sciences United States of America, 108*(34), 13951–13956.

Chantarat, S., Barrett, C. B., Mude, A. G., & Turvey, C. G. (2007). Using weather index insurance to improve drought response for famine prevention. *American Journal of Agricultural Economics, 89*(5), 1262–1268.

Chantarat, S., Mude, A. G., Barrett, C. B., & Carter. M. R. (2013). Designing index-based livestock insurance for managing asset risk in Northern Kenya. *Journal of Risk and Insurance 80*(1): 205–237.

Chantarat, S., Turvey, C. G., Mude, A. G., & Barrett, C. B. (2008). Improving humanitarian response to slow-onset disasters using famine-indexed weather derivatives. *Agricultural Finance Review, 68*(1), 169–195.

Chinvanno, S. (2011). *Developing regional climate change scenario and dilemma in climate change adaptation planning*. Bangkok, Thailand: Mimeo, Southeast Asia System for Analysis, Research and Training (START) Regional Center.

Clarke, D. J., Mahul, O., & Verma, N. (2012). *Index based crop insurance product design and ratemaking* (World Bank Policy Working Paper 5986). Washington DC: World Bank.

Cummins, J. D., & Mahul, O. (2009). *Catastrophe risk financing in developing countries: Principles for public intervention*. Washington DC: The World Bank.

Froot, K. A. (Ed.). (1999). *The financing of catastrophic risk*. Chicago/London: The University of Chicago Press.

Gaiha, R., & Thapa, G. (2006). *Natural disasters, vulnerability and mortalities – A cross-country analysis* (International Fund for Agricultural Development Working Paper). Rome: IFAD.

Hazell, P. B., Pomareda, C., & Valdes, A. (1986). *Crop insurance for agricultural development: Issues and experience*. Baltimore: The Johns Hopkins University Press.

IFRCRCS (International Federation of Red Cross and Red Crescent Societies). (2011). *World disaster report 2011*. Bloomfield, CT: Kumarian Press, Inc.

Intergovernmental Panel on Climate Change. (2007). *Climate change: Impacts, adaptation and vulnerability. Contribution of Working Group II to the 4th Assessment Report of the IPCC*.

Isvilanonda, S. (2009). *Dynamic change of rice production in Thailand*. Bangkok: Lerd Sin Inc.

Mahul, O., & Skees, J. R. (2007). *Managing agricultural risk at the country level: The case of index- based livestock insurance in Mongolia* (Policy Research Working Paper 4325). Washington DC: The World Bank.

Miranda, M. J., Farrin, K., & Romero-Aguilar, R. (2012). *Weather index insurance for developing countries* (Working Paper). Ohio: Ohio State University.

Pannangpetch, K. (2009). *Impacts of global warming on rice, sugarcane, cassava and maize production in Thailand* (Project report. 31 October 2009). Bangkok: The Thailand Research Fund.

Rakwatin, P., Sansena, T., Marjang, N., & Rungsipanich, A. (2012). *Using multi-temporal remote sensing data to estimate 2011 flood area and volume over Chao Phraya river basin, Thailand* (Working Paper). Bangkok: GISTDA.

Ramirez, O. A., Misra, S. K., & Nelson, J. (2003). Efficient estimation of agricultural time series models with nonnormal dependent variables. *American Journal of Agricultural Economics, 85* (4), 1029–1040.

Siamwalla, A., & Na Ranong W. (1980). *Rice handbook* (published manuscript in Thai).

Skees, J. R., Barnett, B. J., & Murphy, A. G. (2008). Creating insurance markets for natural disaster risk in lower income countries: The potential role for securitisation. *Agricultural Finance Review, 68*(1), 151–167.

Swiss Re. (2011a). *Natural catastrophes and man-made disasters in 2011*, Sigma [online]. http://www.swissre.com/sigma/.

Swiss Re. (2011b). *Filling stomachs worldwide with agriculture risk transfer solutions* (Economist Intelligence Unit - Executive Briefing, Singapore Management University. 16 July 2011). Singapore: SMU.

Thailand Fiscal Policy Office. (2010). *Developing a financial instrument for farmers: A case of weather index-based insurance for agriculture in Thailand*. Thailand: Ministry of Finance.

Tucker, C. J., Pinzon, J. E., Brown, M. E., Slayback, D. A., Pak, E. W., Mahoney, R., et al. (2005). An extended AVHRR 8-km NDVI data set compatible with MODIS and SPOT vegetation NDVI data. *International Journal of Remote Sensing, 26*(14), 4485–4498.

WFP, & IFAD. (2010). *Potential for scale and sustainability in weather index insurance*. Rome: IFAD & WFP.

World Bank. (2006). *Earth observation based multi peril crop index development for agricultural insurance– Project development study*. Japan: PASCO Corporation.