CESifo WORKING PAPERS

6530
2017

June 2017

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CESifo

Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
Poschingerstr. 5, 81679 Munich, Germany
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Editors: Clemens Fuest, Oliver Falck, Jasmin Gröschl
www.cesifo-group.org/wp

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CESifo *Working Paper No. 6530*
Category 9: Resource and Environment Economics

A Viable and Cost-Effective Weather Index Insurance for Rice in Indonesia

Abstract

The potentially adverse effects of droughts on agricultural output are obvious. Indonesian rice farmers have no financial protection from climate risk via catastrophic weather risk transfer tools. Done well, a weather index insurance (WII) program can not only provide resources that enable recovery, but can also facilitate the adoption of prevention and adaptation measures and incentivise risk reduction. Here, we quantify the applicability, viability, and likely cost of introducing a WII for droughts for rice production in Indonesia. To reduce basis risk, we construct district specific indices that are based on the estimation of Panel Geographically Weighted Regressions models. With these spatial tools, and detailed district level data on past agricultural productivity and weather conditions, we present an algorithm that generates an effective and actuarially sound WII, and measure its effectiveness in reducing income volatility for farmers. We use data on annual paddy production in 428 Indonesian districts, reported over the period 1990-2013, and climate data from 1950-2015. We use the monthly Palmer Drought Severity Index and identify district-specific trigger and exit points for the insurance plan. We quantify the impact of this hypothetical insurance product using past production data to calculate an actuarially-robust and welfare-enhancing price for this scheme.

JEL-Codes: Q540.

Keywords: index insurance, rice, Indonesia.

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June 2017

1. Introduction

The potentially adverse effects of droughts on agricultural output are obvious. In many high-income countries, the agricultural sector is at least partially protected, but in middle- and low-income countries, where markets and instruments for transferring catastrophic weather risk are nearly always lacking, such protection rarely exists. This lack of financial risk transfer instruments means that losses associated with weather events are greater and economic recovery from them is more prolonged (FAO, 2015). In many countries, recurring weather shocks can induce serious adverse consequences to large numbers of people when agriculture is the main livelihoods of a large proportion of the population. With climate change, these problems are only likely to be exacerbated.

While there is no single solution for managing weather-hazard risks, there is robust evidence to suggest that insurance and other risk-transfer instruments not only provide resources that enable recovery and increase resilience, but also facilitate the adoption of prevention and adaptation measures, hence incentivising the reduction of catastrophic risk (IPCC, 2012; UNFCCC, 2008). Yet, in spite of the clear potential for significant risk transfer that is embedded in financial instruments such as insurance, these are still sorely lacking in most middle- and low-income countries.

Indemnity insurance is plagued by problems of moral hazard, asymmetric information, and high transaction costs, and WII schemes have the potential of overcoming many of these barriers to insurance adoption (Khalil, Kwon, Lall, Miranda, & Skees, 2007; Rao et al., 2015). Given these difficulties in the provision of 'standard' indemnity insurance, a weather-index insurance (WII) may provide an alternative to conventional insurance that can overcome many of the obstacles facing more conventional programs (Nguyen et al., 2017). Increasingly, WII is considered a mainstay of the menu of available risk transfer tools that may assist development as they transfer risk away from the poor and the vulnerable. Consequently, WII schemes have been trialled in several countries; e.g. the CADENA program in Mexico (Janvry, Ritchie, & Sadoulet, 2016).

In this paper, we examine the applicability, viability, and likely cost of introducing a WII for droughts for rice production in Indonesia. Given the size of the sector in Indonesia, and the general importance of rice as a staple source of calories in the region, a viable and cost-effective WII scheme for rice can provide tangible benefits to a large number of people and is clearly worth pursuing. Our findings show that WII could help reduce farmer's revenue fluctuation during drought period up to almost 24% or about Rp. 4 million per hectare[1].

A drought index insurance has been proposed in several countries in Sub-Saharan Africa, South Asia, and North Asia to cover farmers' losses from weather extremes (Rao et al., 2015; Jerry R Skees, Varangis, Gober, Lester, & Kalavakonda, 2001; Tadesse, Shiferaw, & Erenstein, 2015). These initiatives have yet to make significant inroads in implementation in any developing country. There are multiple barriers to implementation that have nothing to do with the design of the marketed schemes, but some of the details of these schemes make them difficult to implement. The purpose of this paper is to design a WII scheme that minimises basis risk – one of the more frequently mentioned design barriers – and test the scheme's viability to cover drought risk for rice farming in Indonesia.

One of the most important barriers for index insurance is basis risk. Basis risk is the possibility that the weather index used for triggering insurance payments does not sufficiently correlate with actual damage. This can lead to both type I and type II errors.[2] Our aim here is to minimise basis risk by constructing district specific indices that are based on spatial modeling and the estimation of Geographically Weighted Panel Regressions (GWPR) models. With these tools, and detailed district level data on past agricultural productivity and weather conditions, we construct an algorithm that generates an effective and actuarially sound WII.

As earlier suggested by Cai, Yu, and Oppenheimer (2014) in a different context, the GWPR approach provides us with an improved ability to associate weather dynamics with crop productivity in topographically and climatically diverse study areas. Once we have identified districts for which WII might be viable, we use Standard Deviation and Mean-Semi variance efficiency tests, as in Shi and Jiang (2016), to show that the WII scheme we designed can reduce revenue risks from yield fluctuation due to drought conditions. We finish by quantifying this risk transfer benefit per district, and thus provide an actuarially fair price for this product for each district.

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[1] Assuming the average revenue per hectare was Rp 17 million (US$ 1300). Specifically, we found that maximum WII benefit are attainable for farmers in Sulawesi.
[2] Type I refers to circumstances where payouts are given when no crop failure occurred and type II refers to conditions where farmers endure crop losses without receiving insurance payouts.

This empirical exploration of a viable scheme uses a panel dataset consisting of data about paddy production in 428 Indonesian districts, from the Ministry of Agriculture, annually for the period 1990-2013, and climate data from the United States of National Oceanic and Atmospheric Administration for 1950-2015. We show that the monthly Palmer Drought Severity Index (PDSI) can be used as the main component of the index as it reflects information on both rainfall and air temperature; the PDSI is generally considered a more sensitive and less noisy indicator of drought conditions (Dai, Trenberth, & Qian, 2004). In our modelling, we also include anomalies of sea surface temperatures in the Pacific Ocean (the El Niño - Southern Oscillation ENSO phenomenon), and the Indian Ocean (the Dipole Mode Index DMI) (D'Arrigo & Wilson, 2008; Iizumi et al., 2014; Naylor, Battisti, Vimont, Falcon, & Burke, 2007; Naylor, Falcon, Rochberg, & Wada, 2001). These additional explanatory variables allow us to obtain a more robust estimate of the relationship between climate indices and crop yield in Indonesian districts in order to identify the districts in which such an insurance index may be viable.

2. Background and motivation

Insurance markets are rife with microeconomic market imperfections or failures that make insurance products very difficult to introduce in places where the institutions to overcome these imperfections are lacking. Market failures for conventional insurance include adverse selection, imperfect or asymmetric information, costly verification, moral hazard and the high cost of dealing with correlated risks. Index insurance is an alternative scheme using an observable index to trigger and quantify insurance payments (Jerry R. Skees, Black, & Barnett, 1997) (Barnett, 2004; M. J. Miranda & Farrin, 2012; J. Skees, Hazell, & Miranda, 1999; Jerry R Skees et al., 2001). Unlike conventional insurance that pays damages based on individual assessment of losses incurred, payment in index based insurance is triggered based on an agreed underlying index and a pre-specified threshold, such as a weather parameter (e.g. rainfall or temperature). As such, for WII moral hazard is minimized, and if the index is based on a publicly observed parameter, there are also no information asymmetries (that plague indemnity-based insurance arrangements). Furthermore, as an underlying index is easy to monitor and verify, the verification costs are significantly lower per policy.

2.1 Weather Index Insurance: Empirical Research

Studies of weather index insurance can be found in the early literature of J. Skees et al. (1999), M. Miranda and Vedenov (2001) and (Olivier Mahul, 2001). More recent works introduced new types of WII contracts such as composite index arrangements in China (Shi & Jiang, 2016), and flexible contracts in Kazakhstan (Conradt, Finger, & Spörri, 2015). Alternatives to calculate actuarially appropriate commercial pricing of the insurance products are described in Clarke, Mahul, Rao, and Verma (2012), while some projects focus on a specific peril like drought (Choudhury, Jones, Okine, & Choudhury, 2016; Rao et al., 2015), extreme rainfall (Nieto, Cook, Läderach, Fisher, & Jones, 2010), and high temperature (Spicka & Hnilica, 2013).

Evaluation of a program post-implementation is not common. As an exception, Janvry et al. (2016) examine data from the CADENA crop insurance program in Mexico. They conclude that while the costs of the program seem high, the farmers for whom insurance payments were triggered were later able to cultivate more land (in the following year). They conclude that under potential weather risks (drought, flood and hail) scenarios, the program's benefits outweigh its costs. Similarly, Bertram-Hümmer (2015) evaluated the Mongolian livestock index insurance scheme after payments were triggered for policyholders during the 2009-2010 winter. They also observe better outcomes for those households that purchased insurance, even after accounting for the selection bias in decision to purchase insurance. Without long-term data on risk and outcomes, however, these observations do not confirm the programs are cost effective.

Several reviews of the weather index insurance (WII) literature are available. These include Leblois and Quirion (2013), Tadesse et al. (2015), and Carter, Janvry, Sadoulet, and Sarris (2014). Binswanger-Mkhize (2012) reviews the state of WII initiatives, and argues that while products can potentially have beneficial welfare impact on small farmers who are otherwise not able to adopt other methods for transferring financial risk, these same farmers will find it difficult to afford their participation in these programs. Perhaps as a consequence of this, he observes that these schemes generally have very low take-up rates among their intended farmer/clients. He also argues that the presence of basis risk in WII programs is potentially too high for it to be worth governments financing these programs. He suggests that other social safety nets, like employment generation programs, can have impacts that are more meaningful to the poor in dealing with the presence of adverse weather events.

Because of the possible link between basis risk and the low uptake of many WII schemes, some quantitative assessments have suggested ways to reduce basis risk. Carter et al. (2014), for example, examines this link and recommend pursuing more technological and actuarial innovations that reduce basis risk Others suggest using risk layering, by combining WII with other financial tools such as credit (Tadesse et al., 2015), enhancing strategic government supports (Janvry et al., 2016; Jerry R Skees, Varangis, Larson, & Siegel, 2004) and combining WII insurance with informal risk pooling to reduce basis risk and improve the quality of insurance coverage (Dercon, Hill, Clarke, Outes-Leon, & Seyoum Taffesse, 2014).

The geographical location of the insured area along with the timing of observations of the index obviously influence the estimation of basis risk, as the underlying weather indices are spatially and temporally differentiated. In addressing these spatial and temporal variabilities, researchers have proposed different strategies. Khalil et al. (2007) consider an insurance contract using a spatially uniform climate index constructed based on the El Niño (ENSO) deviations for a regional rainfall index for mitigating flood risks in Peru. Paulson, Hart, and Hayes (2010) apply spatial analysis techniques to address the absence of high-quality data for weather variables – a typical problem in developing countries. Using interpolation methods, they create rainfall histories from a sparse grid of historical data, and demonstrate the effectiveness of using that rainfall-interpolated data in designing insurance policy and rating. Heimfarth and Musshoff (2011) evaluate spatial basis risk using a decorrelation function – a method that incorporates spatial dependence of weather patterns in analysing the correlation of underlying weather index and crop losses at different weather stations; with the aim of developing a WII scheme at the community level in the North China Plains.

Since our study area is large, encompassing a wide variety of environmental and climatological characteristics, it is reasonable to expect that the influence of weather on crop growth will vary across different locations. Earlier research has investigated the variability of the link between weather and agricultural productivity using various methods such as explicit crop modelling or a statistical approach. For example (Ceglar, Toreti, Lecerf, Van der Velde, & Dentener, 2016) analysed the impact of temperature, solar radiation and rainfall variability on wheat and maize yields over 92 French administrative regions. They find notable spatial differences in the effect of the meteorological indices they use on crop yield.

2.2. Spatial Regression Methods

Earlier studies have found heterogeneity in the link between weather and crop yield across different study areas, yet most researchers still estimate ‘global’ regression parameters (by global we mean parameters that apply to the whole geographical area under investigation). Such global estimates can be inaccurate in understanding the correlation between the variables of interest and can therefore lead to imperfect forecasting. To this end, several methods have been developed to produce localised versions of the traditionally global multivariate regressions.

Spatial techniques are more common in ecology, geography and epidemiology, but are increasingly being used in economics and associated disciplines, thanks to the increased availability of geo-referenced data and improved Geographic Information Systems (GIS) software. Several recent papers, in diverse areas of economics, have argued for the importance of spatial estimations (Anselin, 2001; Kelejian & Prucha, 2010; LeSage & Dominguez, 2012; Woodard, Shee, & Mude, 2016). Specifically, this paper is focused on Geographically Weighted Regressions (GWR) as referred to in Brunsdon, Fotheringham, and Charlton (1996); (Cai et al., 2014; Yu, 2010), Fotheringham, Brundson, and Charlton (2002), Yu (2010), and Cai et al. (2014). GWR allows for the estimation of ‘local’ regression parameters while still accounting for the spatial distribution of the data by including geographically proximate observations, appropriately weighted (Brunsdon et al., 1996).

GWR is a methodology that incorporates both spatial heterogeneity and spatial dependence in the observed variables, allowing different relationships to exist at different points within a pre-determined radius around an observation (Brunsdon et al., 1996; Charlton, Fotheringham, & Brunsdon, 2006; Fotheringham et al., 2002). GWR weighs nearby observations more than distant observations using a distance decay function. Earlier works of GWR used cross-sectional datasets (Brunsdon et al., 1996; Charlton et al., 2006), but more recently, some researchers have been using panel datasets as well. Recent examples of papers using GWR panel (GWPR) techniques are Yu (2010) that studied urbanization and regional development in China and Bruna and Yu (2013) that investigated a regional wage equation model in Europe. For our purpose, the most relevant GWPR work is Cai et al. (2014) that analysed spatially varying association between weather condition and corn yield across 958 U.S. counties from 2002 to 2006. No work that we are aware of has applied the GWPR approach in investigating a WII scheme.

2.3. The Study Area: Indonesian Districts

Indonesia is an archipelagic country extending 5,120 km from east to west and 1,760 km from north to south and consisting of about 6000 inhabited islands. Major ones are Sumatra, Java, Kalimantan, Sulawesi and Papua and the main archipelagos include Bali-Nusa Tenggara and the Maluku. Indonesia has 514 administrative districts (98 cities and 416 regencies - as of 2016). Rich volcanic deposits have endowed many of the Indonesian islands with very fertile soils providing ideal conditions for intensive rice agriculture.

Because of its proximity to the equator, climate in Indonesia is very stable year round, with temperatures averaging between 23-25°C in mountain areas and 28-30°C in the coastal plains. The country has only two seasons: wet and dry, though the difference in rainfall between the seasons varies across the regions. For example, Kalimantan and Sumatra experience only slight differences between the seasons, whereas Nusa Tenggara experiences far more pronounced variance in rainfall. Indonesia has abundant rainfall, particularly in west Sumatra, northwest Kalimantan, west Java, and western Papua, although the islands closer to Australia are drier. Monsoons usually blow from the northwest in November to March and from the south then east in June to October. In general, Indonesia has two growing seasons for rice – though in regions where irrigation networks are available like in Java and Bali, rice may be cultivated in three annual cycles. The main growing season starts after the onset of the monsoon, which generally occurs between September and December. Harvest can be as early as January or as late as April, given this uncertainty in the monsoon arrival. The secondary planting season usually begins in April and is harvested in September.

The agriculture sector is an important economic mainstay for the Indonesian economy, providing jobs for more than 40 million people (about 38% of the total labour force), and contributing around 15% of GDP in recent years. In rural areas where almost half of Indonesians live, farming (including livestock and fisheries) is the main source of income for 63% of households. Indonesia has a total area of 191 million ha. About 57 million ha of this land is cultivated with cash crops (palm oil, cocoa, rubber, coffee, spices and tea), food crops (rice, maize and cassava), horticulture (tomato, carrot, banana, mango, mangosteen, chrysanthemum, rose, etc), and livestock (chicken, duck, goat and cattle). Total land area of *sawah* (a wetland for rice cultivation accounting for about 80% of rice grown in Indonesia) is 8.1 million ha. Almost half of *sawah* cultivation is located in five major producing provinces: East Java, West Java, Central Java, South Sulawesi and South Sumatera.

Rice production in Indonesia is the third largest in the world, after China and India, but like these two bigger countries, most of it is consumed domestically. Rice is the main staple food and its production involves 14 million small farmers having on average less than half a hectare of land per household to cultivate. Paddy yield in Indonesia depends greatly on rainfall, as irrigation infrastructure only exists in limited areas. About 17% of cultivated area is irrigated, mostly in Java, and only 10% of this area is irrigated effectively (IFC, 2012). This implies that a large majority of rice farmers are susceptible to drought risks.

2.4. About WII in Indonesia

Agricultural Insurance (AI) in Indonesia is still very limited, even when compared to other countries at a similar stage of industrialization (O. Mahul & Stutley, 2010). Indonesia officially started an insurance program less than 10 years ago through several government-funded pilot projects. Conventional indemnity AI that offers protection to combined-perils coverage like flood, drought, and pest and disease is the most commonly used approach being tested. Evaluation on several smaller pilot programs found these schemes to be unfeasible due to the inherent problems of conventional indemnity programs discussed above (asymmetric information, moral hazard, and high transaction costs). Therefore alternative modalities such as index based insurance are needed to resolve impediments to program implementation (Insyafiah and Wardhani, 2014). Recently, the Government of Indonesia launched the 3rd Economic Package policy in October 2015; the program includes a nationwide subsidised AI scheme for the rice sector. As this program is being trialled for small-scale rice farmers, the government is also modelling alternative types of AI for fishermen and cattle farmers including the possible use of index insurance.

Literature about WII in Indonesia originated in Estiningtyas, Boer, Las, Buono, and Rakhman (2011), a project that assessed the feasibility of a WII for rice production in three villages in Indramayu district using a rainfall index. It concludes that WII can cost-effectively help farmers managing the risks during long drought period. IFC (2012) explored the feasibility of WII for drought for maize production risk in Eastern Indonesia by testing it in two districts. The study found that it is "technically feasible", and that there is a readily identifiable business model to support WII for maize production in the studied areas. Separate research by Kawanishi and Mimura (2015) investigated the feasibility of weather index insurance in the Bengawan Solo River basin, and tested in two districts. They used the correlation coefficients of monthly rice harvest failure and monthly rainfall, but found a significant basis risk problem. They concluded that in that region, a WII scheme may not be an effective tool to manage weather risk. No research that we are aware of has tried to conduct a more comprehensive feasibility study, i.e. one moving beyond considering only a few districts in a very geographically narrowly-defined region. Without such a study, any conclusions about the external validity of an WII program in Indonesia will be very difficult to reach.

3. Research Questions, Data, and Methods

Four sequential questions of interest guide our research methodology: 1) How can we exploit the spatio-temporal variation in the relationships between weather indices and rice paddy yield to understand better the effect of weather variability during planting season on crop productivity at the district level in Indonesia? 2) Which districts show sufficiently robust links between drought indices and rice yields? 3) Can we develop, using the spatially varying relationships between weather indices and crop yield, a WII program for the Indonesian rice sector? 4) Does this WII scheme reduce the variability of income for farmers residing in 'insured' districts?

This research contributes to the literature in two ways: first, there are only a very limited number of papers using GWPR in any economic context, and no one has applied this spatial modelling approach to design WII schemes. By estimating GWPR using GIS tools, we can use the mapping capabilities of the geo-spatial data to display the results and better understand the spatial ordering underlying them. Secondly, the literature about agricultural insurance in Indonesia is still limited and there is no publicly-available work examining the design of a countrywide WII scheme for the rice sector.

3.1. Crop Data

We obtained agricultural statistics from the Indonesian Ministry of Agriculture comprising annual data of harvested area, productivity or yield, and paddy production at district level within the period of 1990 – 2013. For regression analysis, we use yield data of 428 districts in 33 provinces, as we are limited to districts with consistent and complete information on rice production as well as the availability of geographical data for GIS analysis. The official figures come from the survey of the regional offices of the Ministry of Agriculture that regularly collects data of harvested areas every month. Paddy productivity or yield data are collected every season (4 months cycle) using a specific statistical survey on 2.5 x 2.5 meter squared plots by the local offices of the Centre of Statistical Bureau (BPS) and the agricultural offices.

To recognize spatial variability, we calculate the average paddy yield-per planting season in the period of 1990 – 2013 across the observed districts and map the data (See Annex 2). Districts in Java and some parts of Sulawesi and Sumatera dominate high paddy productivity while low productivity is prevalence across districts in Kalimantan and Papua. The low yield ranges from low 1.7 – 1.9 ton/ha in several districts in Central Kalimantan (Palangkaraya, Barito Utara, Gunung Mas, Lamandau) to high yield of 5.8 – 6 ton/ha in several districts in East Java (Malang, Pasuruan, Magetan).

3.2. Weather Data

Weather related factors are the most important determinant for agricultural production in most instances. Here, we focus on the correlation between weather measures and crop yield during planting season.[3] Since we are interested in the effect of drought on crop productivity, our main explanatory variable is the Palmer Drought Severity Index (PDSI) where we also include climate indices – namely the El Nino - Southern Oscillation (ENSO) index and the Indian Dipole Mode Index (DMI) as factors controlling for local weather conditions[4]. While many studies have investigated the obvious effects of local weather and climatic conditions on all stages of the rice growth cycle, a growing body of evidence also reports the impact of global climate patterns like ENSO and DMI on local weather variables, particularly affecting rainfall and temperature (and hence drought risk). Several studies have found significant effect of global climate condition on rice cultivation in Indonesia (D'Arrigo & Wilson, 2008; Naylor et al., 2007; Naylor et al., 2001; Rosenzweig et al., 2014) – See Annex 6 for an example. We obtained weather data from the NOAA - the United States National Oceanic & Atmospheric Administration (NOAA).

Table 1. Summary Statistics data

	Mean	Std Deviation	Min	Max
Administrative				
Area district (Ha)	440,981.1	625,448.2	986.7	4,531,178
Crop Data				
Yield (Ton/Ha)	4.278409	1.075369	.4	8.4

[3] Compared to flood or storm surges, drought is the most dominant climatic hazard that results in considerable losses to the agriculture sector due to natural disasters in Indonesia in the last 4 decades (Lassa, 2012).
[4] In other works like Choudhury et al. (2016), these global climate control variable are considered as to manifest climate change that have significant impact on crop yield.

Indices				
PDSI	-.4105	2.416	-7.5825	7.245
ENSO (ºC)	.0287	.6697	-1.16	1.74
DMI (ºC)	.2636	.3885	-.464254	1.0963

The PDSI was firstly developed by Palmer (1965) to measure the cumulative deficit in atmospheric water balance using information on precipitation, temperature and altitude in US regions. The latter version of the PDSI has been widely used worldwide for monitoring and forecasting drought incidents, analysing the impact of climate variations, and also for index insurance (D'Arrigo & Wilson, 2008; Dai et al., 2004; Jerry R Skees et al., 2001; Wu, Chen, Wang, & Sun, 2015). For this research, we use the monthly mean self-calibrated Dai's PDSI gridded dataset, which is updated until December 2014 and available online at the US Earth System Research Laboratory website.[5] Dai et al. (2004) first introduced this monthly dataset of PDSI from 1870 to 2002 using historical precipitation and temperature data for global land areas on a 2.5° grid on both latitude and longitude.

The current calibrated dataset accounts for the effects of radiation, humidity and wind speed in addition to rainfall and temperature. We assign each district a PDSI value per year in PDSI gridded area as shown in Annex 3 and Annex 4. It shows average PDSI value during planting season (September – December) 1990 – 2013. In Annex 5., we include a common reference of PDSI classification that indicates the severity of a wet or dry spell which generally ranges from -6 to +6, with negative values denoting dry spells and positive values indicating wet spells. Following (D'Arrigo & Wilson, 2008), we use PDSI values during the planting season (Sept-Dec) to detect drought incidence that affect crop yield in the following year.

The El Niño/Southern Oscillation is a global phenomenon that represent a recurring pattern of climate variability in the Equatorial Pacific. It signifies anomalies in both sea-surface temperature and sea level pressure (Southern Oscillation) where the anomalies for warming period are referred to as El Niño and the cooling periods are referred to as La Niña. In this paper, we control for ENSO using the Oceanic Niño Index 3.4 - it measures the average of temperature anomalies over Central-Eastern Equatorial Pacific (5°S–5°N, 170°W–120°W). We use historical monthly data for ENSO since 1950 which is available online from the Climate Prediction Centre.[6]

[5] http://www.esrl.noaa.gov/psd/data/gridded/data.pdsi.html
[6] http://www.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ONI_change.shtml

The Indian Ocean Dipole Mode Index (DMI), measures irregular differences in the temperature between two areas in the Western and the Eastern Indian Ocean. Like the ENSO, it may relate to rice productivity in Indonesia because of its relationship with rainfall. A positive phase of DMI is indicated by lesser than average temperatures and greater precipitation in the Western Indian Ocean region, and with a corresponding cooling of waters in the Eastern Indian Ocean. This pattern tends to cause droughts in Indonesia and Australia. The negative phase of the DMI brings about the opposite conditions, with warmer water and greater precipitation in the Eastern Indian Ocean, and cooler and drier conditions in the Western part.

3.3. The Spatial Models

Our data is a panel of weather observations and paddy yield of 428 districts for a 24-year period (1990-2013). By using panel GWR, we are able to utilize both the cross-sectional and time-series dimensions of the panel of observations we have, to account for both time-invariant differences between districts (such as soil and climate conditions). In order to remove non-weather variable effects such as policy changes and technological improvement that might change over time of observation, we detrended the paddy yield data using the Hodrick-Prescott filter (Baum, 2004).[7] We present the deviation between detrended yield and actual yield in Annex 1. For comparison purposes, we also used original yield data in estimating the weather effect on yield variation. In doing so, we specify the model with time trends to control for the effects of other variables than weather (such as technology improvement). The estimation results using the original data are not identical with estimation using the detrended yield data but show similar patterns on the statistically significant areas (see Annex 13 for visual overview, detail estimation results are available upon request).

3.3.1 Fixed Effects, Spatial Auto-Regressive, and Spatial Error Models

Fixed Effect modelling is the most common regression technique used to analyse the relationship between climatic change and crop yield (see Deschenes and Greenstone (2007) for an example). The model is specified as:

$$y_{it} = \beta_{0i} + \sum_k \beta_k x_{itk} + \varepsilon_{it} \qquad (1)$$

[7] Previous work have shown that de-trending agricultural yield time-series data is useful for isolating the impact of technological changes on crop yield, particularly for actuarial purposes, see for example, Jerry R. Skees et al. (1997).

where i represents a district and t indicates year; y_{it} denotes paddy yields for district i at year t; x_{itk} denotes the k weather indices for district i at year t; β_k is a weather-index coefficient that is constant across districts and across time; β_{0i} denotes time-invariant fixed effects; and ε_{it} is the error term. Previous research does not support the assumption that β is indeed constant across districts, and we find that assumption unattractive if we are to develop a WII product that minimizes spatially-differentiated basis risk.

A second approach – spatial regression modelling – recognises the dependency between nearby observations in spatial data through the covariance structure of the error terms but still provides only global parameter estimates (Anselin, 1992, 2001; LeSage & Dominguez, 2012). These models consider spatial spill-overs in the dependent variable, and specify the endogenous variable corresponding to a cross sectional unit in terms of a weighted average of variables corresponding to other cross sectional units, plus a disturbance term (Kelejian & Prucha, 2010). Although these methods recognize and incorporate spatial dependency, they have limited use when the relationships between the variables of interest do vary over space (β is not uniform across districts). We therefore proceed with a Geographically Weighted Regression analysis that allows us to obtain district specific estimates for β, and thus investigate a potentially different WII scheme for each district.

3.3.2 Geographically Weighted Regression (GWR)

GWR uses neighbouring observations for estimation of a local regression at each point in space with a subsample of spatially-weighted data, weighted according to the proximity of each observation to each regression point. Consider a linear (global) regression model:

$$y_i = \beta_0 + \sum_k \beta_k x_{ik} + \varepsilon_i \qquad (2)$$

GWR extends this global regression by allowing local parameters for estimation:

$$y_i = \beta_{i0} + \sum_k \beta_{ik} x_{ik} + \varepsilon_i \qquad (3)$$

where y_i is the observation of the dependent variable at geographic location i, β_{ik} is the coefficient parameter of the k^{th} independent variable at geographic location i. x_{ik} denotes the k^{th} predictor variables at location i and ε_i denotes the error term. Although the GWR model (3) is a simple extension of the global linear model in (2), estimating the coefficients in model (3) is more difficult since there are not enough degrees of freedom. GWR assumes that coefficient parameters are not random, but rather that they are a deterministic functions of location in space

(Fotheringham et al., 2002). To this end, a Weighted Least Square (WLS) method is used to calibrate regression model (3) with the assumption that observed data near to location i have more of an influence in the estimation of β_{ik} than do data located farther away (geographically). Ordinary Least Square (OLS) minimizes the sum of square residuals. In WLS, a weighting factor W, is applied to each squared difference before minimizing sum of square residuals, so that the deviations of some predictions incur more of a penalty than others. Estimation of parameters can then be written in the form:

$$\hat{\beta}(i) = (X^T W(i) X)^{-1} X^T W(i) Y \quad (4)$$

where $\hat{\beta}$ is an estimate of β, $W(i)$ is an n x n spatial weighting matrix, its diagonal elements are zero and the diagonal elements are the geographical weighting of each of the n observed data for regression point i. The weighting matrix is computed for each point i according to a decay function based on the assumption that the observations nearer to the regression point are assigned more weight to represent their larger influence than observations further away and the weight decays linearly in distance.

The next step in estimating the GWR is choosing the bandwidth (the radius in which observations are still included for each regression). There are mainly two types of kernel functions used to determine the shape and extent of the bandwidth: Fixed and Adaptive. A circular neighbourhood of fixed (ad-hoc) radius is where each local regression analysis includes all observations within the fixed distance from the regression point, and the Adaptive algorithm is when a flexible algorithm is used to pre-determine a constant number of neighbouring sample points. Both types of functions employ the same principle of declining weights with distance. Equally important for the GWR is determining the distance to the regression point that will be used as it defines how much each observation will be weighted (Fotheringham et al., 2002; Yu, 2010). In this paper, we specify a spatial weighting function using the fixed method of Gaussian kernel (Fotheringham et al., 2002). For the bandwidth parameter, we select the optimal distance to derive bandwidth as generated by the GIS program. In exploring best results (more study areas that show statistically significant weather effects) and for comparison purposes, we also tested several regression estimates using different type of kernel and bandwidth methods (see Annex 16. for summary tests report).

Most GWR works use cross-sectional analysis, but new methods that exploit panel data using GWR can potentially give more accurate inference of model parameters and reveal new findings that might be hidden under the standard cross-sectional model described above. The first study to use Panel GWR was Yu (2010), examining the relationship between urbanization and regional development in Greater Beijing. Later on, Bruna and Yu (2013) investigated the effect of Market Potential on regional wages of European regions using GWPR in a particular context of wage equations. They showed how spatial change across Europe was particularly high for Portugal, Spain, South of France and North of Italy. Most recently, Cai et al. (2014) investigated the effect of weather on corn yield for 958 U.S. counties from 2002 to 2006 with a panel GWR and found that temperature tends to have negative effects on corn yields in warmer regions and positive effects in cooler regions.

In general, the panel GWR model considers the earlier framework with an additional temporal component (t) in each independent variables and error:

$$y_{it} = \beta_{i0} + \sum_k \beta_{ik} x_{ikt} + \varepsilon_{it} \qquad (6)$$

Compared to the Fixed Effects model equation (1), the panel GWR allows the vector of coefficients β to vary across i (district) but not across t (time). We assume that bandwidths and the spatial weighting function are time-invariant, because spatial relationships among the districts do not change over time (especially in a short panel such as ours). Since the estimation will include both spatial and temporal observations, the matrix dimension becomes nt x nt and all observations used in each local model are weighted by the time invariant spatial weight function.

In order to convince the reader that the panel GWR should be our preferable model, we also estimated the other models described earlier, including estimation of fixed effects panel model and the standard spatial AR models with global coefficients. Accurate estimation—a good statistical fit—is important in this paper's context, as our aim in estimating these equations is to identify a model that will reduce spatially-sensitive basis risk when constructing a WII scheme.

3.4. Actuarial Analysis: Design and Valuation of index insurance

As the GWR estimates a different model for each district, we can focus only on those districts for which the weather indices (in particular the PDSI) have a statistically significant predictive power for crop yield in the multi-variate model. Having thus identified the subset of districts for which it is feasible to design an index insurance based on the indices we have, the next step is determining the optimal trigger and exit thresholds of the underlying weather index that will trigger the payment of compensation, and the cap on that compensation, respectively.

3.4.1. Cluster Analysis for the Thresholds

We apply a model-based clustering analysis to determine the optimal trigger and exit thresholds of the PDSI index as for drought identification as introduced by Choudhury et al. (2016). Cluster analysis is a data analysis technique for organizing observed data into clusters, based on combinations of relevant factors. It classifies observations so that each object is very similar to each other within the cluster with respect to some criterion. In this paper, our underlying weather variable for the WII is the PDSI drought index; as we reported, it has a statistical association with paddy yield data. Therefore, we focus on these two variables in identifying index thresholds (trigger and exit) using cluster analysis. See detailed discussion about model-based cluster analysis in Fraley and Raftery (2012).

As the more negative PDSI value spells drier conditions (see Annex 5), it is reasonable to assume that the lower the PDSI value the higher the probability of crop loss. With the cluster analysis tool, we can group observations of higher PDSI value (wet condition) based on similarity with higher yield observations and dry condition or lower PDSI value with lower paddy yield observations. The resulting clusters of observations should then exhibit high internal homogeneity and high external heterogeneity (Choudhury et al., 2016). In other words, these clusters are formed based on maximizing the similarity of observations within each cluster while also maximizing the difference between the clusters.

For comparison, we also run analyses to determine triggers of the WII using logistic regression models which are solved by Bayesian estimation (as in Khalil et al. (2007). With this method, we found the index thresholds are a bit lower than the index (trigger) resulting from the cluster analysis.[8]

3.4.2. Pricing the Index Insurance

Pricing an insurance contract should reflect the degree of the risk that is being insured. Consider the following standard cost equation of the commercial pricing insurance:

Price of Insurance = Expected Annual Loss + Expense Loads + Risk Factor

[8] The greatest difference is found in Kalimantan. The trigger level for Kalimantan is almost one and a half points PDSI lower than the cluster analysis trigger (see Annex 12 for the detail results). This resulted in less coverage and a lower insurance premium.

where Price of Insurance is the insurance premium, Expected Annual Loss (EAL) is the expected probability of annual loss – i.e., the average insurance claim payment that is paid out each year. Expense Loads considers all costs of covering administrative and operational expenses of providing the insurance, such as costs for: loss assessment, monitoring, administration, product delivery, and capital costs/profits. Risk Factor is an additional load to the premium usually charged by a risk-averse or risk neutral insurance company to protect it again the possibility that it is under-valuing the premium (Smith & Watts, 2009). The expense loads and risk factor are assumed to be proportional to the present value of the EAL.

In an index insurance contract, there are significant transaction cost savings that can be transferred to the insured party in the form of a lower premium, compared to a conventional indemnity-based insurance. Therefore, in calculating the price of WII, we exclude some components of expense loads such as cost for controlling adverse selection (e.g. collection/surveys of farm-level information), cost for conducting loss assessment, and cost for controlling moral hazards (e.g. monitoring farm). We assume that administration cost is lower since WII has simple and uniform and contracts do not need to be tailored to each policyholder). We also assume that there are fewer costs associated with product delivery and product development.

In this study, considering the proposed WII scheme is new and the targeted clientele is made up of small-scale rice farmers, it is reasonable to assume that the WII scheme will receive support from the government through load factors subsidy.[9] Thus, here we only use actuarially fair premium or pure risk premium as the price of insurance assuming away the loading factors. The actuarially fair premium—henceforth 'premium'—is calculated as the expected value of the future payoff of the insurance discounted by the risk-free interest rate. Consider:

$$\text{Premium} = \textit{Present Value}\ (EAL) = (e^{-rt}) \tag{8}$$

In general, the pricing of the WII product is based on the underlying payment structure, when should a payment be triggered by the index, and the probability distribution that describes the possible observed valued of the index. The following equation expresses a payment:

[9] In many cases, and for many reasons, private sector risk transfer mechanism are not available, and this justifies public sector investments in weather-related agricultural insurance (Olivier Mahul, 2001; M. Miranda & Vedenov, 2001; Jerry R Skees et al., 2004)

$$Payout = \begin{cases} IA & if\ PDSI_A \leq PDSI_E \\ IA\left(\frac{PDSI_T - PDSI_A}{PDSI_T - PDSI_E}\right) & if\ PDSI_E < PDSI_A \leq PDSI_T \\ 0 & if\ PDSI_A \geq PDSI_T \end{cases}$$

where IA is the insured amount (we set IA equals to an average cost of inputs such as seed, fertilizer and pesticide) and $PDSI_A$ denotes actual PDSI in planting season (Sept-Dec), $PDSI_T$ is trigger, a PDSI threshold where a payout starts, $PDSI_E$ denotes exit threshold where the maximum payout = insured amount (IA) is paid.

The critical step in pricing WII is to estimate EAL (the average payout each year). We use historical data for the PDSI, as the underlying weather index, to simulate what the insurance cost would have been had the insurance product been in place in previous years.[10] In this paper, the expected annual loss is calculated using normal probability and numerical integration as applied in Choudhury et al. (2016):

$$EAL = IA \int_0^{PDSI_E} f(PDSI_E) d_{PDSI_E} + \int_{PDSI_E}^{PDSI_T} IA\left(\frac{PDSI_T - PDSI_A}{PDSI_T - PDSI_E}\right) f(PDSI_A) d_{PDSI_A} \qquad (9)$$

$$EAL = IA \int_0^{PDSI_E} f(PDSI_E) d_{PDSI_E} + \frac{IA}{PDSI_T - PDSI_E} \int_{PDSI_E}^{PDSI_T} PDSI_T\, f(PDSI_A) d_{PDSI_A} - \frac{IA}{PDSI_T - PDSI_E} \int_{PDSI_E}^{PDSI_T} PDSI_A\, f(PDSI_A) d_{PDSI_A}$$

Given normal mean and standard deviation, we then can calculate probability of PDSI that exceeded thresholds $PDSI_T$ and $PDSI_E$:

$$EAL = IA\big(F(PDSI_E)\big) + \frac{IA}{PDSI_T - PDSI_E}\Big(PDSI_T\big(F(PDSI_T) - F(PDSI_E)\big)\Big) - \frac{IA}{PDSI_T - PDSI_E} \int_{PDSI_E}^{PDSI_T} PDSI_A\, f(PDSI_A) d_{PDSI_A}$$

To solve the third terms, we apply numerical integration on the historical PDSI data to get an approximate value of PDSI actual ($PDSI_A$) that falls between the trigger and exit thresholds.

3.5. Efficiency Test to Measure WII's Risk Reduction Capability

Finally, we test the robustness of WII in reducing the underwritten risk using two different measures of the revenue of rice farming without and with WII - the standard deviation (SD) and the mean-semivariance (MSV). We analyse the reduction of SD and the increase in MSV during the 24 years observed period if WII were to be implemented to measure the

[10] Historical loss cost data may not be adequate for estimating future indemnities if the insurance product covers losses from extreme but infrequent events which may or may not have occured over the observed period.

effectiveness of the scheme in lessening rice income variability during drought periods. We implicitly assume the investment portfolio of the representative farmer in each district consists only of rice-production assets and the proposed WII contract, and they have no other risk transfer tools. A rice farmer who buys a WII product may expect to have lower returns on his/her investment portfolio, due to a loaded premium, but he/she may expect to have reduced risk. This is measured by the variance of the returns on the portfolio.

Firstly, we analyse the effectiveness of WII to hedge the risk by comparing the distribution of revenues of rice farming without WII and with WII at each district. We can measure it by looking at the standard deviation of revenue per hectare from the paddy farming without insurance, R_0 - defined as: $R_0 = pQ$. Q denotes paddy yield (kg/ha), a function of the stochastic weather variable PDSI. p is expected postharvest crop price (Rp/kg), which in this paper we set constant at Rp.4,000/kg. In the second scenario where a crop insurance is purchased, a farmer may get compensation of a pay-out (F_T) if the underlying weather variable exceeds the trigger while he also has to pay the insurance premium (F_0). The payout is a function of the underlying index weather variable x, thus the revenue per hectare from paddy farming with WII, R_1, becomes: $R_1 = R_0 + F_T - F_0$.

Next, we apply the mean semivariance (MSV) model to assess how effective the WII is at reducing income shocks during drought periods. The difference versus the SD measure is that MSV counts only observations below the expected value. While variance or SD can give insight about the extent of risk exposure of a portfolio, MSV focuses on estimating the possible negative effect (loss) -on average- on a portfolio. Minimizing downside risk is of potential interest to risk-averse households, as most small-scale farmers are. We start by calculating deviations of rice revenue below the average and ignore those observations above the mean. This semivariance between revenue of rice farming without WII and with WII represents the threat of loss. Consider the following:

$$U_i = \begin{cases} R_i - E(R) & if\ R_i < E(R) \\ 0 & if\ R_i \geq E(R) \end{cases}, \quad \text{and} \quad \sigma_{semi}^2 = \frac{1}{n}\sum_{i=1}^{n} U_i^2 \qquad (10)$$

where U_i denotes the investor's utility, R_i is farming revenue (calculated both with and without WII), $E(R)$ is expected value of the revenue (without and with WII), n denotes total number of observations and σ_{semi}^2 denotes the semivariance of revenue below the expected value. To this end, we apply MSV to measure the shortfall of rice revenue risk during drought weather condition by analysing the exposure level of revenue risk V that is relative to semivariance:

$$V = E(R) \ - \frac{1}{2} k\sigma_{semi}^2 \qquad (11)$$

where, k is the coefficient of relative risk aversion and V denotes the revenue risk. Here we simulate different k = 0.1, 0.2, and 0.3. The parameter k indicates the risk-averseness of the investor (Eeckhoudt & Gollier, 1995). From the equation above we know that a higher V value means smaller (or reduced) semivariance (likelihood of loss), and vice versa, therefore in the next section we will compare V values to assess WII's capability as a risk hedging tool.[11]

4. Result and Discussion

4.1. Spatially Varying Relationship of Weather Pattern and Paddy Yield

For the cross sectional GWR model regression, results indicate very few districts that are positively pseudo-significant at 5% significance level.[12] Since general climatic conditions are very similar across provinces, and the important variation we are interested in is in the weather variability during the rice growing seasons, this absence of differentiation between results arising the cross-sectional estimation may not be surprising. The panel estimation results are shown in Table 2. We start with the three regression models that assume global (constant) coefficients across districts (in columns 1-3). We estimate the model with fixed effects, and with two spatial models. In all three, we find robust evidence of an association between changes in paddy yields and the changing levels of the weather indices (PDSI, ENSO and DMI). In addition, the spatial regression models also show the highly significant coefficients ρ and λ that define the spatial dependence in the observed variables as shown in Table 2.

Results for the benchmark GWR Panel model that accounts for the spatial differences in the estimated coefficients are presented in Table 2 column 4. Since we cannot show the estimated coefficient for each district, we average the coefficients by quartiles. These confirm the spatial heterogeneity we hypothesized, as the interquartile ranges of the coefficients (for

[11] The MSV model in this paper refers to an approach recently applied in Shi and Jiang (2016) to evaluate the efficiency of an index insurance in hedging revenue risk against extreme weather conditions in paddy production in China.

[12] Pseudo-significance for the GWR refers to the t-statistic for the coefficient associated with a (local) regression point.

PDSI, ENSO and DMI) are all larger than two times the standard errors of the global fixed effect model and the spatial regression models.

Table 2. Estimation Results Fixed Effect, Spatial Regression Model and GWR Panel of 428 Districts in Indonesia during 1990 - 2013

Dependent Variable: Paddy Yield (Ton/Ha)	Fixed Effect	Spatial Lag (SAR)	Spatial Error (SEM)	GWR Panel Q1	GWR Panel Median	GWR Panel Q3
	(1)	(2)	(3)		(4)	
PDSI	0.0307***	0.0184***	0.0264***	0.0020	.0239	0.0457
	(0.00172)	(0.00146)	(0.00220)			
ENSO (ºC)	-0.0271***	-0.00955*	-0.0251***	-0.0855	-0.0378	0.0112
	(0.00576)	(0.00486)	(0.00755)			
ENSO2	-0.0741***	-0.0383***	-0.0530***			
	(0.00480)	(0.00409)	(0.00652)			
DMI (ºC)	0.311***	0.165***	0.226***	0.2354	0.2993	0.3416
	(0.00911)	(0.00810)	(0.0126)			
Constant	4.080***					
	(0.00458)					
ρ		0.476***				
		(0.00856)				
λ			0.477***			
			(0.00887)			
σ²		0.0809***	0.0819***			
		(0.00115)	(0.00117)			
N	10272	10272	10272		10272	
R-squared	0.141	0.151	0.139		0.764	
Number of District	428	428	428		428	
Number of Years	24	24	24		24	

Note: a complete result of GWR Panel regression parameters for districts that are positively Pseudo-Significant at 5% Significance Level is presented in Annex 14.

The spatial distributions of GWR Panel's coefficient estimates PDSI are presented in Figure 1, showing strong relation between variability of drought indices PDSI and paddy yields in several regions in Eastern and South Eastern part of Sumatera, major part of Sulawesi, middle part and Southern part of Kalimantan and eastern part of Papua. A comparison of Figures 2 and 3 shows that in for the GWR Panel model estimates, there are more pseudo-significant coefficients for PDSI (214 districts - about 50% of the total observed districts) than in the local regression model where each district is estimated separately. The results of the local regressions of each district show that the PDSI coefficient is statistically significant in only 140 districts (compared to 214 for the GWR Panel).

In Figure 4, that zooms in on the significant regions, we see that paddy yields are positively correlated with the PDSI in almost all districts in Sulawesi, the districts in the central part of Sumatera, central to southern part of Kalimantan, and the eastern part of Papua.

Figure 1. Spatial Distribution of GWR Panel Coefficient Estimate PDSI Planting Season

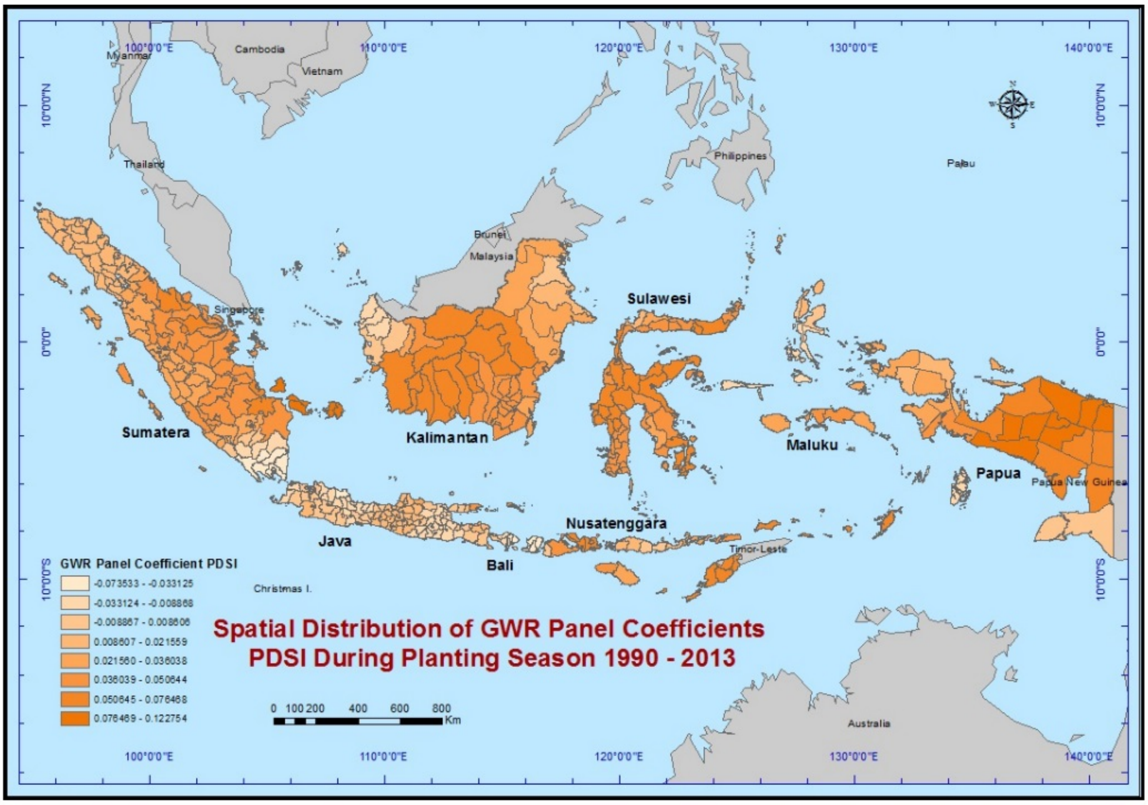


Figure 2. Spatial Distribution of Local Coefficient Estimate PDSI Planting Season of Districts that are Pseudo-significant at 5% Significance Level

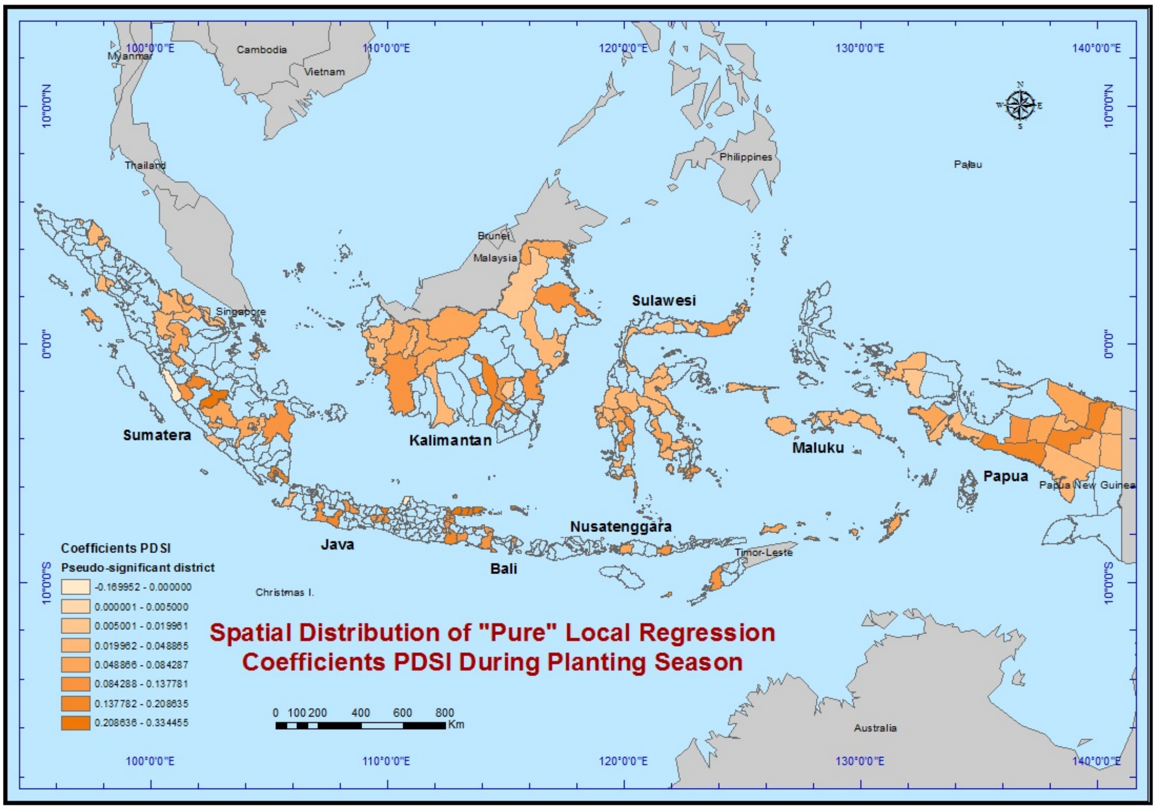


Figure 3. Spatial Distribution of GWR Panel Coefficient Estimate PDSI Planting Season of Districts that are Pseudo-significant at 5% Significance Level

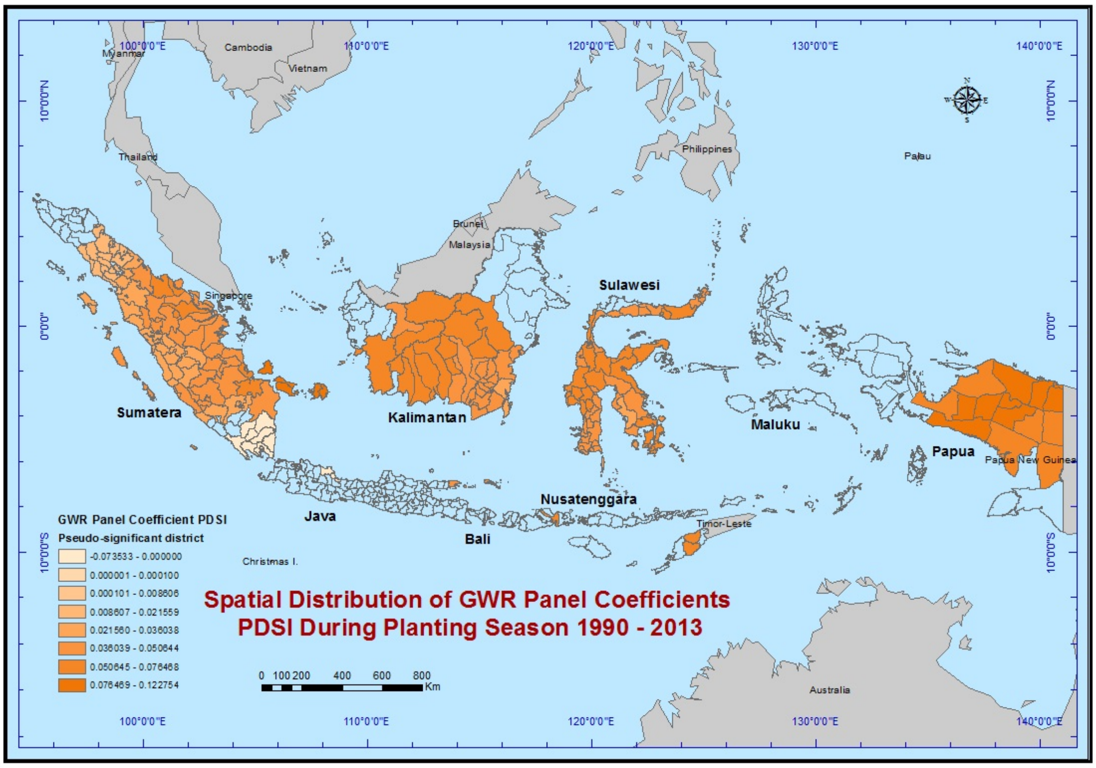
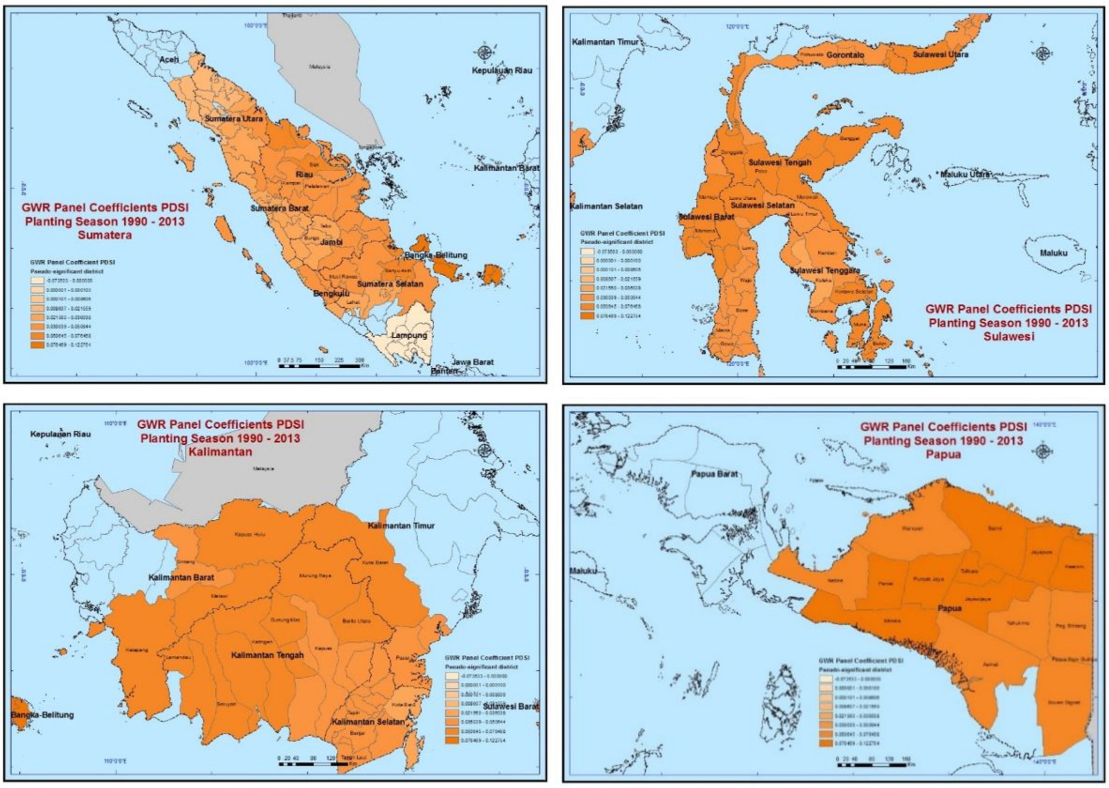


Figure 4. Spatial Distribution of GWR Panel Coefficients PDSI in Planting Season of Districts in Major Islands that are Pseudo-significant at 5% Significance Level



The PDSI index is not statistically associated with paddy yields in districts in Java, Bali, Nusa Tenggara and Maluku, except within a few districts that appear randomly distributed across these islands (Figure 3). For Java and Bali, this is most likely due to the extensive irrigation networks that are in use there, ameliorating the effects of drought conditions on paddy productivity. For the districts in Maluku and Nusa Tenggara, the lack of statistical power may be hindering any precise identification, as these districts are in small islands and therefore have very few neighboring districts and consequently fewer degrees of freedom as each district-specific regression uses fewer observations.

It is interesting to note—see Annex 9—that paddy yields are correlated positively with the Indian El Niño (DMI) in most of Kalimantan and all parts of Sumatera, Java-Bali and Sulawesi while there is no evidence that climate impact exists at districts further away in northern Kalimantan, all Maluku and all of Papua. For the Pacific El Niño (ENSO), the phenomenon's impact on paddy yield is found in the southern part of Sumatera and in only a small part of northern Java while a moderate effect is experienced in the northern part of Sumatera and much of Java (Annex 10). These El Niño results are consistent with previous findings (D'Arrigo & Wilson, 2008; Naylor et al., 2001). A complete set of of estimated parameters for each district from the GWR Panel is available in Annex 14.

4.2. Designing Weather Index Insurance

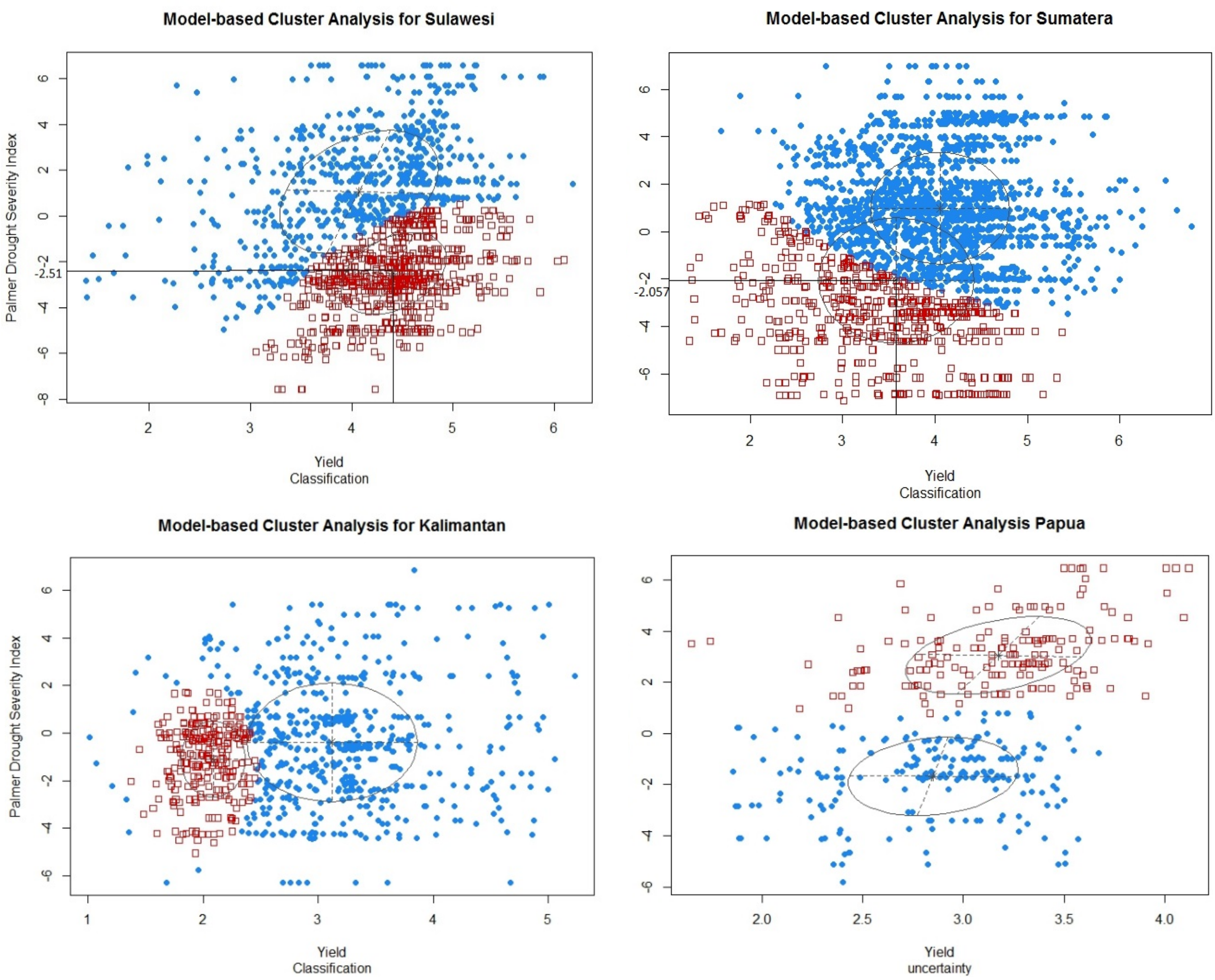
Building on our findings that establish a substantial degree of correlation between the observed weather indices and crop yield (R-squared 0.764), we now turn to the design of the WII product we propose using the PDSI index. We can now, using our previous results, identify the districts for which such an insurance product is viable. In this case, payments will be triggered when the PDSI exceeds a predetermined threshold level (the Trigger) until maximum indemnity payment level is reached at a higher PDSI (the Exit). At the PDSI range between the Trigger and Exit levels, we assumed that paddy yield decreases progressively resulting in more and more crop loss (and more and more indemnity payment).

To determine the underlying threshold points (Trigger and Exit), we first cluster the districts with pseudo-significant coefficient estimates for the PDSI in the major islands where GWR Panel results show statistical significance. These include districts in Sulawesi, Kalimantan, Sumatera and Papua. We don't include actuary calculation for districts in Java, Bali, Nusa Tenggara, and Maluku since the GWR Panel shows little evidence that PDSI is closely related to yield losses in these regions.

Next, we apply the model–based cluster analysis described in the previous section in order to group lower PDSI values during planting season (September to December) and lower crop yields to determine the Trigger and Exit level of the index insurance; as in (Choudhury et al., 2016).

Figure 5 shows the results of model-based cluster analysis that produces two clusters in the sample islands Sulawesi and Sumatera (result for other islands are presented in Annex 14). The lower (red) cluster represents the combination of lower PDSI and paddy yield, hence we set this level as the "trigger". We set the expected value of PDSI in the lower (red) cluster as the predetermined threshold for the payment trigger where indemnity payment start to be provided by the insurance policy and the minimum value of PDSI in the lower (red) cluster as the predetermined threshold for exit where total sum-insured is reached.

Figure 5. Trigger of Underlying Index PDSI for Districts in Island of Sulawesi, Sumatera, Kalimantan and Papua using Model-Based Cluster



Once we set the underlying index, we calculate the premium for the index insurance that will be applied at each major island.This uniform pricing strategy for each major island, rather than specific pricing at each and every district, is implemented as it is significantly more convenient and we believe its simplicity will be attractive for commercial insurers. After all, an important feature of an index insurance distinguishing it from conventional insurance is indeed its simplicity. Using equation (9), we calculate the average future payouts (EAL) during 24 years of observation, using the historical observed drought index (1990-2013), assuming the insurance scheme was offered in that period. We then determine the premium by calculating the present value of these payouts as described in equation (8).[13]

[13] See Choudhury et al. (2016).

We next set the following assumptions in analysing the risk reduction achieved by the proposed WII in smoothing farmers' reveue during drought. We assume the price of paddy (GKG/dry unhusked rice) is constant – Rp. 4,000/kg, and set the maximum insured amount at Rp. 2,000,000/Ha - which is equal to the averaged costs for inputs (seed, fertilizer, pesticide) and land lease of rain-fed paddy farming.[14] The parameters of the proposed insurance contracts are presented in Table 3.

Table 3. Parameters of Weather Index Insurance Using Drought Indices PDSI for Rice Production in Major Islands in Indonesia

Island	Insured (Rp)	Trigger (PDSI)	Exit PDSI)	Tick (IDR / point index)	Average Payout (Rp)	Premium (Rp)
Sumatera	2,000,000	-2.057	-6.907	412,371	22,104	21,000
Kalimantan	2,000,000	-1.092	-6.265	386,623	112,661	107,000
Sulawesi	2,000,000	-2.510	-7.583	394,244	24,504	24,000
Papua	2,000,000	-1.675	-5.808	483,910	37,525	36,000

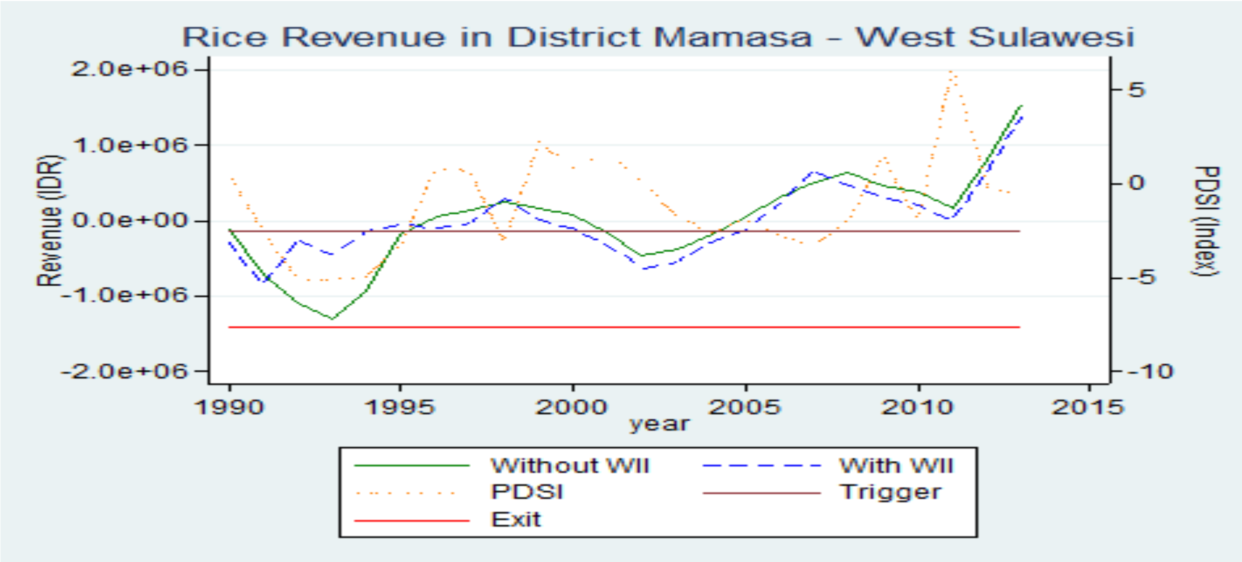
4.3. The Efficiency of Weather Index Insurance using the PDSI

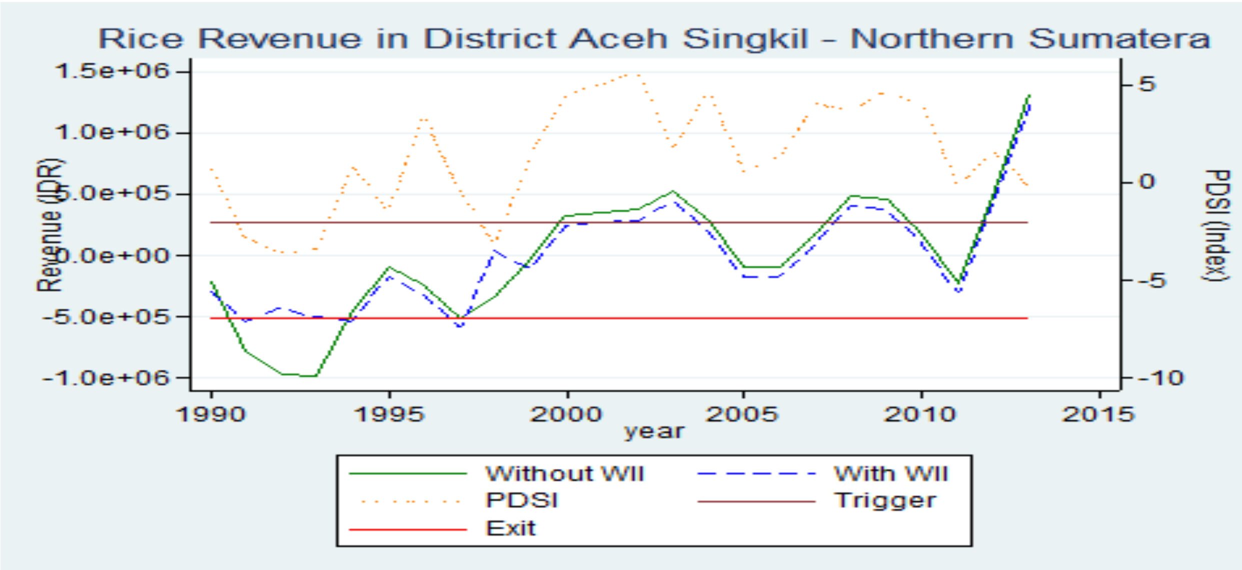
Lastly, we examine whether the drought index insurance as designed above has the potential to assist farmers in dealing with the income variability they face because of weather extremes. First, we compare the actual revenue from paddy farming without index insurance to the hypothetical revenue from paddy farming with index insurance during the same observation period: 1990-2012; see Figure 6.

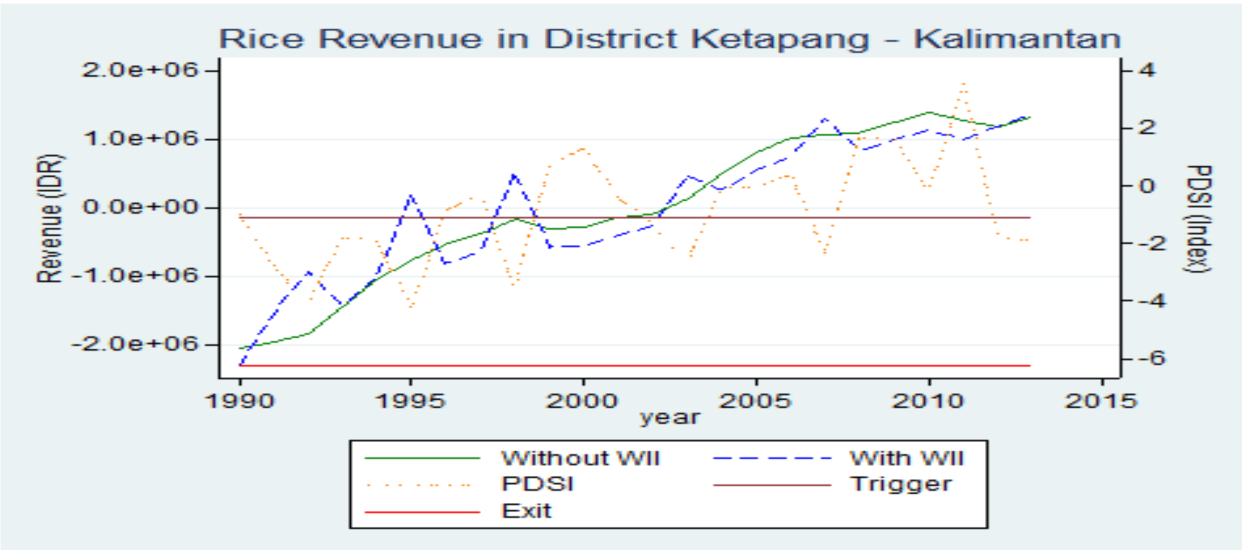
We observe that the variance of crop revenue from paddy farming with and without insurance are distinct and that farmers with insurance appear to be able to stabilize their income during drought events like in 1991 – 1995 in Mamasa district (top panel). The same situation also occurs over 1991 – 1993 for Aceh Singkil district (middle panel), and in many years between 1990 and 2008 for Ketapang district (bottom panel).

Figure 6. Paddy Revenues Without and With Index Insurance in selected districts in Sulawesi, Kalimantan and Sumatera

[14] (http://www.bps.go.id/linkTabelStatis/view/id/1855)


Rice Revenue in District Mamasa - West Sulawesi
2.0e+06
1.0e+06
0.0e+00
-1.0e+06
-2.0e+06
Revenue (IDR)
5
0
-5
-10
PDSI (Index)
1990
1995
2000
2005
2010
2015
year
Without WII
With WII
PDSI
Trigger
Exit


Rice Revenue in District Aceh Singkil - Northern Sumatera
1.5e+06
1.0e+06
5.0e+05
0.0e+00
-5.0e+05
-1.0e+06
Revenue (IDR)
5
0
-5
-10
PDSI (Index)
1990
1995
2000
2005
2010
2015
year
Without WII
With WII
PDSI
Trigger
Exit


Rice Revenue in District Ketapang - Kalimantan
2.0e+06
1.0e+06
0.0e+00
-1.0e+06
-2.0e+06
Revenue (IDR)
4
2
0
-2
-4
-6
PDSI (Index)
1990
1995
2000
2005
2010
2015
year
Without WII
With WII
PDSI
Trigger
Exit

Next, we present in Table 4 a selection of results for 20 districts obtained from our revenue calculations and the change in revenue variability (standard deviation) with and without insurance based on the historical observations. The districts selected are the ones where the variability declined between 7% - 23.7%. Total revenue per hectare without insurance, R_0, is derived by multiplying unit paddy price with predicted yield (equation (7)). Revenue paddy farming per hectare, R_1, is calculated from the sum of R_0 plus indemnity payment from the index insurance and minus premium (as defined in equation 7). Annex 15 presents the results for all other districts.

Table 4. Comparison Revenue with and without Insurance in selected Districts

No	District	Island	Without Insurance (IDRx1000)	With Insurance (IDRx1000)	SD Change
1	Mamasa	Sulawesi	16,445 (625.9)	16,588 (477.6)	-23.70%
2	Polewali Mandar	Sulawesi	19,403 (726.1)	19,546 (599.4)	-17.45%
3	Parigi Moutong	Sulawesi	19,478 (794.3)	19,657 (679.5)	-14.46%
4	Gorontalo	Sulawesi	18,222 (782.6)	18,344 (703.7)	-10.07%
5	Pohuwato	Sulawesi	18,964 (1,044.4)	19,144 (942.5)	-9.76%
6	Pare-pare	Sulawesi	17,326 (1,349.3)	17,469 (1,243.6)	-7.83%
7	Soppeng	Sulawesi	21,129 (2,458.5)	21,272 (2,272.9)	-7.55%
8	Barru	Sulawesi	19,031 (1,602.7)	19,174 (1,488.3)	-7.14%
9	Aceh Singkil	Sumatera	13,885 (532.7)	13,946 (429.2)	-19.43%
10	Langsa	Sumatera	15,663 (565.0)	15,725 (473.5)	-16.20%
11	Medan	Sumatera	17,737 (559.9)	17,799 (469.4)	-16.17%
12	Kampar	Sumatera	11,367 (1,307.9)	11,718 (1,104.8)	-15.53%
13	Aceh Tamiang	Sumatera	16,783 (669.7)	16,845 (575.2)	-14.12%
14	Pakpak Bharat	Sumatera	13,357 (659.0)	13,419 (576.1)	-12.57%
15	Sijunjung	Sumatera	15,983 (1,266.8)	16,176 (1,114.0)	-12.06%
16	Tebing Tinggi	Sumatera	17,854 (600.0)	17,916 (534.7)	-10.88%
17	Pekanbaru	Sumatera	10,816 (2,510.6)	11,168 (2,311.9)	-7.91%
18	Aceh Tenggara	Sumatera	16,550 (1,009.5)	16,612 (932.6)	-7.62%
19	Samosir	Sumatera	18,346 (827.8)	18,408 (769.2)	-7.07%
20	Ketapang	Kalimantan	10,847 (1,109.2)	11,005 (1,020.5)	-8.00%

Note: Revenues are average values during 1990-2013 and standard deviations, SD, are shown in parentheses. Table shows results from selected districts with regards significant SD decrease. See Annex 15. for results all districts. Unit Revenue and Standard Deviation is in IDR, Indonesian Rupiah

Summarizing Annex 15., we found that reduction of farm income volatility occurs in major parts of Sulawesi (79%), Papua (64% of districts), Sumatera (51% of districts) and some part of Kalimantan (29% of districts). In Java's districts, the variability actually increased by up to 40%, indicating that the insurance contract does not reduce the risk. This incongruence may be because the PDSI is not a good predictor for agricultural productivity in an irrigated and intensely managed agricultural sector such as paddy rice in Java; in these cases, index insurance using a signal like the PDSI does not work well.

Finally, we apply the MSV model to assess how WII can reduce income exposures during drought. We analyse revenue risk, V, with and without WII at different level of *k* (the measure of risk-averseness) at the same selected districts as in Table 4. As can be seen in Table 5, farmers with insurance (WII) have higher revenue risks (V in eq. 11) relative to farmers without insurance in all risk-averseness (k) levels. As described in equation (11), revenue risks (V) has negative link with (mean-semi) variance. Therefore, a higher value of revenue risk (V) corresponds to lower (semi)variance of revenue. We can also see in Table 5. that the higher the value of k (level of risk averseness), the larger the gap between WII and non-WII farmers. This, maybe not surprisingly, indicates that more risk-averse farmers may be more interested in WII than less risk-averse farmers.

Table 5. Efficiency Test using Mean-Semivariance Model

District	k = 0.1		k = 0.2		k = 0.3	
	V without Insurance (million IDR)	V with Insurance (million IDR)	V without Insurance (million IDR)	V with Insurance (million IDR)	V without Insurance (million IDR)	V with Insurance (million IDR)
Bitung	16.423	16.573	16.400	16.559	16.378	16.544
Minahasa Utara	13.866	13.933	13.848	13.920	13.829	13.906
Sintang	19.377	19.525	19.352	19.505	19.327	19.485
Dumai	15.643	15.709	15.624	15.694	15.604	15.679
Rokan Hilir	17.718	17.783	17.698	17.768	17.679	17.753
Bengkalis	11.327	11.682	11.287	11.647	11.247	11.611
Siak	19.450	19.633	19.423	19.610	19.396	19.586
Boalemo	16.758	16.824	16.734	16.804	16.709	16.783
Pekanbaru	13.336	13.402	13.315	13.384	13.294	13.367
Majene	15.938	16.135	15.892	16.094	15.846	16.053
Polewali Mandar	17.836	17.900	17.818	17.884	17.799	17.869
Mamasa	18.199	18.324	18.175	18.303	18.152	18.283
Rokan Hulu	18.933	19.117	18.903	19.090	18.872	19.063
Kampar	10.807	10.968	10.766	10.930	10.726	10.892
Tana Toraja	10.733	11.091	10.650	11.013	10.567	10.936
Barito Timur	17.275	17.421	17.224	17.373	17.174	17.325
Pinrang	16.508	16.573	16.466	16.535	16.425	16.496
Banggai	21.034	21.185	20.939	21.099	20.843	21.012
Tojo Una-una	18.967	19.114	18.903	19.054	18.839	18.993
Luwu Utara	18.323	18.387	18.300	18.367	18.276	18.346

Note: Revenue risk V without and with insurance at different level of *k*. Revenue risk V with insurance is higher than revenue risk V without insurance. A higher revenue risk V value corresponds to lower risk exposure (Shi & Jiang, 2016).

5. Conclusion and Recommendation

The impacts of natural hazards on livelihoods have increased substantially in the past few decades within many locations. A number of factors are at play, but at least some of this increase is attributable to increasing weather risk caused by climatic changes; these have particular effects in middle- and low-income areas that are more reliant on agricultural production. Given the increased risk to important agricultural sectors, disaster risk-transfer strategies can therefore be an important tool to reduce the impact of natural hazards on farmers' incomes and its variability.

Weather index insurance (WII) may be one form of insurance that can be productively used to accomplish some of the goals set out by the 2015 Sendai Framework on Disaster Risk Reduction. As the Sendai Framework recognised, insurance can be a tool that enables the transfer of risk from vulnerable households to established financial institutions and markets. Weather index insurance has been piloted and implemented in several developing countries. According to its advocates, it can provide an effective approach to improve emergency response to weather-related catastrophes as well as facilitate a role in adaptation to climate change and disaster recovery; see recent experiences in, for example, Mongolia and Peru for cold waves and floods, respectively, and the inter-country African Risk Capacity scheme for droughts (Collier, Skees, & Barnett, 2009; UNFCCC, 2008).

Here, we investigated the relationships between paddy yield and weather indices during the planting season by exploiting the spatio-temporal variation of both, including applying a Geographically Weighted Panel Regression method to account better for the spatial component of this variation than previous studies have achieved. This allowed us to identify the Indonesian regions in which a WII scheme would be most effective. We found that paddy yield variations in many districts in Sulawesi are strongly positively associated with the PDSI index. The same was also true in Central Sumatera, Central and Southern Kalimantan, and Eastern Papua. We did not establish a similar association between the PDSI and rice productivity over much of the rest of Indonesia, including most districts in Java, Bali, Nusa Tenggara and Maluku.

The detailed spatial information, on varying responses of paddy to fluctuations in weather indices, allows us to tailor specific WII schemes for different targeted districts in Indonesia. This island-specific tailoring—most importantly by setting island-specific trigger and exit points—results in more effective risk reduction.

What type of scheme may be appropriate for islands in which the PDSI is not tightly correlated with rice production is an open question. Alternative weather measures or satellite-based observational data can be explored as potential parametric anchors. We leave these possibilities for future research.

Beyond the use of our finding in constructing WII programs, one can also use our evidence on the correlations between the PDSI, the ocean oscillation indices and rice farm income, to develop other risk reduction programs. For example, the prioritization of investment in irrigation infrastructure may be guided by the relationship we uncovered between the drought index (the PDSI) and crop productivity in some districts and not others.

We conclude that a PDSI index insurance program may be suitable for implementation in more drought-sensitive areas like in Sulawesi, some parts of Sumatera and some smaller parts of Kalimantan. We found that the insurance contract reduced the decline in revenues of participating farmers during drought periods in rice production districts in Sulawesi such as in Bitung, Minahasa Utara, Polewali Mandar and in Sumatera districts such as in Dumai, Rokan Hilir, and Bengkalis. We emphasize Sulawesi as a priority for a pilot implantation of this program because of the strong significant evidence of the association between the drought index variability and paddy yield in almost all districts on that very big island. Our findings also show that WII in Sulawesi has the highest financial potential of hedging risks while decreasing the volatility of income.

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