Using a regional climate model to develop index-based drought insurance for sovereign disaster risk transfer

Roman Hohl
International Finance Corporation, World Bank Group, Washington, District of Columbia, USA and Tropical Marine Science Institute, National University of Singapore, Singapore, Singapore
Ze Jiang
Tropical Marine Science Institute, National University of Singapore, Singapore, Singapore
Minh Tue Vu
Glenn Department of Civil Engineering, Clemson University, Clemson, South Carolina, USA, and
Srivatsan Vijayaraghavan and Shie-Yui Liong
Tropical Marine Science Institute, National University of Singapore, Singapore, Singapore

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Abstract

Purpose – Examine the usability of rainfall and temperature outputs of a regional climate model (RCM) and meteorological drought indices to develop a macro-level risk transfer product to compensate the government of Central Java, Indonesia, for drought-related disaster payments to rice farmers.
Design/methodology/approach – Based on 0.5° gridded rainfall and temperature data (1960–2015) and projections of the WRF-RCM (2016–2040), the Standardized Precipitation Index (SPI) and the Standardized Precipitation Evapotranspiration Index (SPEI) are calculated for Central Java over different time spans. The drought indices are correlated to annual and seasonal rice production, based on which a weather index insurance structure is developed.
Findings – The six-month SPI correlates best with the wet season rice production, which generates most output in Central Java. The SPI time series reveals that drought severity increases in future years (2016–2040) and leads to higher payouts from the weather index structure compared to the historical period (1960–2015).
Practical implications – The developed methodology in using SPI for historical and projected periods allows the development of weather index insurance in other regions which have a clear link between rainfall deficit and agricultural production volatility.
Originality/value – Meteorological drought indices are a viable alternative for weather index insurance, which is usually based on rainfall amounts. RCM outputs provide valuable insights into future climate variability and drought risk and prolong the time series, which should result in more robust weather index insurance products.

Keywords Drought risk mitigation, Climate change, Regional climate model, Standardized precipitation index, Weather index insurance, Sovereign disaster risk transfer
Paper type Research paper

Introduction

Catastrophic weather events are felt most at farm level but can have severe financial consequences for the agricultural supply chain including agricultural banks, input suppliers, processors, cooperatives and logistic companies and for government agencies that provide

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ad-hoc disaster relief and administrate redevelopment budgets. The lack of opportunities to transfer weather risks in the agricultural supply chain to insurance and capital markets can severely limit the evolution of efficient agricultural credit markets and value chains, undermine future investments and hinder efforts for rural poor in developing countries to emerge from poverty (Miranda and Farrin, 2012).

In developed countries, conventional indemnity-based crop insurance is widely available with well-known structural issues that include moral hazard (Smith and Goodwin, 1996), adverse selection (Just *et al.*, 1999) and systemic risk (Miranda and Glauber, 1997). Further, indemnity-based crop insurance causes high costs related to risk assessment at farm level, administration and loss adjustment, while often, substantial government subsidies are required to make insurance affordable. In developing countries that are often characterized by small farm sizes, index-based crop insurance, and particularly weather index insurance, has been promoted as an efficient risk transfer instrument. While index-based insurance largely mitigates moral hazard and adverse selection (Berg and Schmitz, 2008) and reduces costs as indemnities are directly settled on the indices (Barnett and Mahul, 2007), it induces inherent basis risk, which results in a failure of index insurance to provide indemnities that perfectly match the losses of the insured (Doherty and Richter, 2002).

The main categories of indices used in agricultural insurance can be divided into (Hohl, 2019) (1) weather indices where climate data are used to define insurance payouts mainly rainfall and temperature as, for example, used in India (Clarke *et al.*, 2012) and parts of Africa (e.g. Tadesse *et al.*, 2015); (2) yield indices where regional crop yields define payouts relative to expected yields as, for example, used in the United States (Ramsey and Goodwin, 2019) and India (Bhushan and Kumar, 2017); (3) satellite indices that are based on the Normalized Difference Vegetation Index (NDVI, e.g. Turvey and Mclaurin, 2012; Bokusheva *et al.*, 2016) and *f*-covers (Roumiguié *et al.*, 2015) for drought-related reductions in forage quantity and increased livestock mortality as used in Mexico and Uruguay (World Bank, 2013) and Kenya (Jensen *et al.*, 2015); (4) climate indices as used in Peru for drought occurrences related to sea surface temperature anomalies during El Niño years (Mortensen and Block, 2018); and (5) model-driven indices including the Water Requirement Satisfaction Index (WRSI) that reflects drought risk as used in Africa (African Risk Capacity, 2019). Additionally, outputs of mechanistic crop models have been explored for crop insurance purposes (e.g. Castañeda-Vera *et al.*, 2015).

Despite significant efforts to develop index-based crop insurance (especially weather index insurance) at micro-level in developing countries, uptake rates remain low (e.g. Dercon *et al.*, 2014), except where heavy premium subsidies are available or because governments pressure insurers to develop and offer mandatory products for lower-income groups (Miranda and Gonzalez-Vega, 2011). Constraints of weather index insurance in developing countries include the basis risk at micro-level (Weber *et al.*, 2015), difficulties to access weather and agricultural production data, inconsistencies in the data along with the affordability of insurance by farmers and a general unfamiliarity and mistrusts of producers towards insurance. Further, short time series of climate data on which the indices are developed can lead to an underestimation of risk, particularly when large and extreme losses have not been experienced historically. As a result of the shortcoming of index-based insurance at micro-level, research and project development is increasingly focussing on meso- and macro-level risk transfer in supporting financial institutions and governments to provide solutions to the rural poor which, in turn, can benefit from insurance products at aggregated levels (Miranda and Gonzalez-Vega, 2011).

In Indonesia, the agricultural sector is highly exposed to natural disasters and is dominated by smallholders that mainly produce rice and corn as staples. While recently efforts have been undertaken to establish *ex ante* risk financing including crop insurance (Pasaribu, 2010), provincial governments face an increasing financial burden to support farmers affected by natural disasters and to import additional agricultural commodities to maintain food security. Although well-developed agricultural markets can largely substitute government disaster payment schemes, index insurance offers provincial governments immediate protection against large volatilities in budgets for disaster payments to agricultural producers affected by natural disasters.

This study explores the development of a macro-level index insurance product that indemnifies the government of Central Java, Indonesia, for disaster payments to rice farmers following severe droughts. Based on historical climate data (1960–2015) and projections from a regional climate model (RCM) (2016–2040), two widely used meteorological drought indices are computed to obtain a time series of 81 years (1960–2040).

Macro-level index insurance

To overcome the obstacles in farm-based crop insurance in developing countries, some thoughts have been given how to transfer weather risk at meso- and macro-level (Binswanger-Mkhize, 2012; Miranda and Farrin, 2012) following the concept of pooling risks for risk aggregators. While meso-level insurance focusses on risk transfer with agricultural intermediaries in the supply chain, macro-level insurance targets weather risks of governments and non-governmental organizations that administrate disaster relief funds and procure additional agricultural commodities from international markets after the impact of natural catastrophes. Macro-level insurance supports governments in a more cost-effective use of resources, improved planning and better preparedness for catastrophes and lower reliance on international donors for ad-hoc assistance in the aftermath of catastrophes (Hess *et al.*, 2006), stability in disaster and emergency food procurement budgets and more effective risk layering in the agricultural production system. Unlike micro-level insurance, macro-level insurance is used by a single government entity and can use complex structures that capture the relationship between weather variables and agricultural losses in an optional way while reducing basis risk. Additionally, macro-level insurance can make use of existing distribution channels such as disaster payment schemes to reach the beneficiaries in the most efficient way. However, macro-level structures with a single national index can fail to capture regional disasters and require a contingency plan to assure that insurance proceeds are distributed timely to affected farmers and to prevent misuses of indemnities (Miranda and Farrin, 2012). Miranda and Farrin (2012) suggest that macro-level products are more likely to succeed if they are implemented in collaboration with international donor groups and relief agencies as it prevents a lower risk that donor support is reduced.

Governments have increasingly been using macro-level risk transfer products to cover public infrastructure from earthquakes and hurricanes through insurance-linked securities such as catastrophe bonds (Linnerooth-Bayer and Hochrainer-Stigler, 2015). The use of a catastrophe bond for agricultural risks has theoretically been discussed for a state-wide reduction in cotton yields in Georgia, USA (Vedenov *et al.*, 2006) and for drought risk in Kenya (Sun *et al.*, 2015). Despite its potential, only a few macro-level insurance structures have been implemented for sovereign risks in agriculture. In Mexico, the federal government covers local governments through FONDEN for reconstruction of local infrastructure, the implementation of temporary employment programmes and direct payments of farmers for income losses following natural disasters (Skees *et al.*, 2002). One of the first index-based sovereign risk transfers occurred in Ethiopia in 2006, through a cumulative rainfall index that provided insurance payouts to the government in case of drought losses to wheat, millet, cowpea and maize with over 67,000 households benefiting from timely payouts (Barrett *et al.*, 2009). In 2008, the government of Malawi entered into a derivative contract that was based on the Malawi Maize Index and consisted of WRSI computations, to obtain, in case of a severe drought, immediate funds to procure additional maize from international markets (Syroka, and Nucifora, 2010). In 2016, the government of the Chinese province of Heilongjiang started buying index-based reinsurance to cover income volatility of poor rural households in 28 counties from flood, excessive rainfall, drought and low temperature based on weather and satellite data (Swiss Re, 2016).

With climatological disasters becoming possibly more severe under climate change scenarios and with governments implementing more comprehensive disaster risk financing frameworks, the demand for macro-level risk transfer of agricultural risks from the public sector is likely to increase further.

Regional and global climate models

Essentially, Global Climate Models (GCM) and Earth System Models (ESM) are the most advanced tools that are currently available for modelling the response of the global climate system to increasing radiative forcing at large temporal and spatial scales. GCMs and ESMs are mathematical representations of the climate system on a three-dimensional numerical grid with equations relating physical processes in the atmosphere, ocean, cryosphere and land surface. These models have been applied for various studies, ranging from simulations of present-day climate to the study of paleoclimates and possible future climate conditions under the effect of variations in global forcing (Giorgi, 1995). Climate data from GCMs are of coarse spatial resolution (typically 100–200 km) and a downscaling procedure is required to obtain data at a finer resolution (5–10 km) (IPCC, 2007). The most common downscaling approaches rely on either statistical/empirical or dynamical methods. The dynamical method employs a higher-resolution regional limited area model, known as a Regional Climate Model (RCM), that is driven by GCM outputs.

Drought impacts on rice production in Indonesia

Indonesia is one of the main agricultural producers globally and largely relies on domestic food staples (especially rice) for its growing population. In recent years, agriculture has been contributing 13.5% to the gross domestic product while employing 34% of the labour force (OECD, 2017). Several studies have found that the Indonesian rice production is strongly influenced by annual and interannual variations of rainfall driven by the El Niño Southern Oscillation (ENSO) and the Austral-Asia Monsoon (Amien *et al.*, 1996). Liyantono *et al.* (2012) found that in East Java, the main factor of agricultural production sustainability is rainfall variability that is caused by the ENSO with El Niño years having below-average rainfall (often resulting in drought) and La Niña years with above-average rainfall (flooding). Various studies have shown that ENSO-related droughts have significant consequences for agricultural output, rural income, staple food prices and famines in Indonesia (e.g. Naylor *et al.*, 2007). The occurrence of an El Niño typically leads to a delay in the wet season of two or three months and consequently, a delay of rice harvests (Amien *et al.*, 1996). On average, the potential impacts of drought due to weak and moderate El Niño occurrences reduced rice yields in Indonesia by 40% (Surmaini *et al.*, 2015). Naylor *et al.* (2001) showed that in Java, the strong 1997/98 El Niño caused a reduction in rice areas of 700,000 ha and a production loss of 3.2m tons, which is equivalent to one-fourth of the total rice volume that was annually traded in international markets (1971–1998).

Under climate change conditions, Indonesia is likely to experience temperature increases of 0.8°–1.1°C by 2030 with a high likelihood for the rainy season to end earlier and its length to shorten (IFPRI, 2011; IPCC, 2013). Climate change can affect rice production in Indonesia in various ways including: (1) each 1°C temperature increase lowers rice quality and can lead to yield losses of 1.3m metric tons or 10–25% of the total production; (2) a 30-day delay in the onset of the wet season might decrease rice yields by 6.5–11% in West/Central Java and East Java/Bali and may ultimately prevent farmers from planting two consequent rice crops; and (3) a 60-cm sea level rise can severely reduce rice yields in coastal areas (MER, 2015). Climatological disasters, including El Niño-related droughts, accounted for more than 40% of all disbursements from the government's reserve funds between 2010 and 2016 (BNPB, 2017).

In Indonesia, several measures have been implemented to reduce drought losses and include: (1) drought detection and monitoring through meteorological drought indices and satellite-based vegetation health indices; (2) establishment of early warning systems to more reliably predict the onset of El Niño events to manage food security policies; and (3) changing the paradigm of sovereign disaster support from post-disaster funding and the reliance on emergency contributions from the international community towards *ex ante* disaster risk financing. As part of risk financing, the government started piloting indemnity-based rice insurance in 2010, covering flood, drought and certain pests and diseases during the wet and dry seasons (Pasaribu, 2010). Despite the government subsidizing 80% of the rice insurance premium, the insurance penetration remains low with considerable costs to distribute insurance to smallholders. Most farmers rely on ad-hoc disaster payments while the increase of government disaster spending for climate disasters, of which a majority is provided to the agricultural sector, has created concerns about budget stability for many provincial governments and increased the interest for index-based sovereign disaster insurance against drought.

Data

The development of weather index insurance requires a consistent time series of weather and loss proxies such as crop yield data that allows the construction of robust and reliable indices. For this study, the development of a meteorological drought index that compensates the government of Central Java for losses of severe droughts requires historical rainfall and temperature data at a reasonable temporal and spatial resolution, projected rainfall and temperature data from an RCM and historical rice production statistics and farm gate rice prices.

Agricultural data

For the province of Central Java, annual rice yield, harvested area and production are available from the Ministry of Agriculture (1986–2015). Additionally, seasonal rice yield, harvested area and production are obtained from the Central Java government (2006–2015) and include the following seasons: (1) a wet season (planting in January and harvest in April), (2) dry season 1 (May–August) and (3) dry season 2 (September–December). A brief analysis of irrigation intensity levels (FAO, 2016) shows that rice production areas are mainly irrigated along the coast and allow therefore the planting for three seasons and are rain-fed in the upper lands where rice is grown in two seasons.

Seasonal and annual rice production shows an increase overtime, which is driven by both larger areas harvested and higher average rice yields. However, the short time series, particularly for seasonal production (2006–2015), does not allow a meaningful trend analysis. As disaster payments to farmers affected by natural disasters are based on rice production deficits (rather than yield reduction), seasonal rice production (1986–2015) is chosen for this study as a loss proxy to validate the suitability of meteorological drought indices for weather index insurance. Farm gate prices for wet paddy in Central Java, which are the prices that farmers receive in the domestic market, are available from the Central Java government as annual averages. For this study, the 2016 farm gate price for INR 4,000/kg (US$300/ton) is used.

Historical climate data

As access to climate data from a sufficiently large network of weather stations is difficult in Indonesia and due to the requirement for gridded climate data to match the RCM outputs, different open-source gridded climate data sets are first investigated for the province of

Central Java. The gridded climate data from the Climatic Research Unit (CRU, series 3.24.01, Harris *et al.*, 2014) is found to be most suitable for this study and includes monthly rainfall and temperature at a 0.5° spatial resolution (1960–2015). CRU uses weather station data from different sources including the Global Historical Climatology Network (Lawrimore *et al.*, 2011), which is an integrated database of climate summaries from land surface stations across the globe and CLIMAT (Jones and Moberg, 2003).

CRU data have been used for climatological analyses in Indonesia (e.g. D'Arrigo and Smerdon, 2008), and a comparison of the CRU data set with Indonesian weather station records shows a good agreement, particularly for Sumatera and Java (Supari and Sopaheluwakan, 2016). Further, CRU data have been validated over Southeast Asia and been used as inputs into RCMs (e.g. Ratna *et al.*, 2017) and in studies of climate change and the occurrence of El Niño events in Southeast Asia (e.g. Thirumalai *et al.*, 2017).

Regional climate model data

This study uses the Weather Research and Forecasting (WRF) model (Skamarock *et al.*, 2008), which is one of the most widely applied climate models, with numerous applications in Southeast Asia (e.g. Chotamonsak *et al.*, 2011; Raghavan *et al.*, 2016) including climate change studies in agriculture (e.g. Jiang *et al.*, 2019). The physics configurations of the WRF model used in this study are based on an earlier investigation by the Tropical Marine Science Institute of the National University of Singapore (Raghavan *et al.*, 2016) and include rainfall and temperature simulations at a 20-km spatial resolution for Java, Indonesia. The WRF model was initially driven by the global reanalyses ERA-Interim data (Berrisford *et al.*, 2011) for model performance assessments. Subsequently, the model is driven by three global climate models that are MPI ESM-MR, CSIRO-ACCESS1.3 and MRI-MIROC5 from the Coupled Model Intercomparison Project Phase 5 (Taylor *et al.*, 2012) that formed part of the downscaling exercise to assess changes in future climates at regional scales.

For this study, the baseline historical climate is set for 1986–2005 while the future climate is based on the Representative Concentration Pathways (RCP) scenario 8.5 [1] for 2016–2040. The RCP scenarios include a set of emission scenarios from the Intergovernmental Panel on Climate Change (IPCC) and are based on possible net radiative forcing by the end of the century under the influence of anthropogenic climate change [2].

Methods

Methods applied in this study involve (1) establishing a reliable meteorological drought index that has low data requirements, reflecting drought risk for rice production and can be computed from historical (1960–2015, historical period) and projected gridded climate data (2016–2040, projected period); (2) developing a weather index insurance structure that is based on the meteorological drought index that correlates best to annual or seasonal rice production shortfall; and (3) comparing payouts of the weather index with rice production shortfalls to determine the suitability of the weather index structure for sovereign disaster risk transfer.

Drought indices

A large variety of indices are used for operational and research applications to detect, monitor and model droughts and include (1) meteorological indices such as the Standardized Precipitation Index (SPI) and the Palmer Drought Severity Index (PDSI), (2) satellite-derived vegetation health indices including the NDVI, the Enhanced Vegetation Index (EVI) and the Vegetation Condition Index (VCI) and (3) combinations of different indices (Zargar *et al.*, 2011).

The SPI (McKee *et al.*, 1993) is one of the most accepted and widely used meteorological drought indices and has been recommended by the World Meteorological Organization (WMO) as one of the most suitable indices for drought monitoring and climate risk management of different time spans (WMO, 2009). Conceptually, the SPI is equivalent to the *Z*-Score in statistics and is formulated as (Patel *et al.*, 2007)

$$\mathrm{SPI}ij \approx \frac{Xij - \mu ij}{\sigma ij}$$

where SPIij is the SPI of the ith month at the jth timescale, Xij is the total rainfall for the ith month and the jth timescale, μij and σij are long-term mean and standard deviation associated with the ith month and the jth timescale. The method to compute SPI is described in detail in Guttman (1999) and is here briefly summarized through (1) preparing a time series for a continuous period of historical precipitation records (ideally over 30 years) and a desired time interval (e.g. one month); (2) fitting a Gamma function to the historical records to define the relationship of probability to precipitation; and (3) calculating the probability of any observed precipitation with an estimate of the inverse normal distribution to obtain the precipitation deviation for a normally distributed probability density with a mean of zero and a standard deviation of unity. The scale of the SPI ranges from $>+2$ (extremely wet) to < -2 (extremely dry) with values between -0.99 and $+0.99$ defined as near normal. A meteorological drought is typically defined with an SPI being continuously below a value of -1.

Although precipitation is often the main variable that determines the onset, duration, intensity and end of a drought (e.g. Heim, 2002), a shortcoming of SPI is that it only uses rainfall and ignores other variables such as temperature, evapotranspiration, wind speed and soil water holding capacity, which can influence the severity and duration of a drought. As a response, the Standardized Precipitation Evapotranspiration Index (SPEI, Vicente-Serrano *et al.*, 2010) has been developed and while it is based on the SPI procedure, it uses the difference between potential evapotranspiration (PET) and precipitation. PET is computed through a simplistic water balance equation using surface temperature, air humidity, soil incoming radiation, water vapor pressure and ground–atmosphere latent and sensible heat fluxes (Allen *et al.*, 1998). The scale of the SPEI for rainfall deficit is the same as for SPI.

The use of meteorological indices including the SPI has been explored for crop insurance by Leblois and Quirion (2013) and for weather index insurance by Fischer *et al.* (2012). In Argentina, a pilot insurance programme was based on six-month SPIs calculated from weather station data to compensate dairy farmers for reduced milk production in case of drought occurrence (SPI < -2) and/or excessive rainfall events (SPI $>+2$) (Mercosur Group, 2016). In Indonesia, the Meteorological, Climatological and Geophysical Agency (BMKG) operationally computes SPI to monitor and quantify drought risk [3] for the national and province governments. SPI has been used in Southeast Asia to quantify drought in GCM applications (e.g. Vu *et al.*, 2018).

Due to their wide use, simplicity and high acceptance, SPI and SPEI are explored as meteorological drought indices in this study. First, SPIs and SPEIs are computed from the monthly CRU gridded precipitation and temperature data (1960–2015, 0.5° spatial resolution) for all 23 grid cells that cover the province of Central Java and are subsequently totalled over all grids to obtain one monthly value for the province. To quantify the relationship between the SPIs and SPEIs and seasonal as well as annual rice production shortfalls, the indices are aggregated over different months that cover the rice growing periods including the wet season (January–April), dry season 1 (May–August), dry season 2 (September–December) and the annual period (January–December). While indices of shorter durations show more seasonal rainfall trends and reveal patterns of seasonal droughts, annual indices reflect more long-term precipitation deficits and cycles. For the projected rainfall and temperature data from the WRF-RCM, the six hourly data are first aggregated to monthly timescales, after which the same procedure is used to calculate SPI and SPEI values as has been applied for the historical gridded climate data. As a result, different SPI and SPEI time series are obtained for the historical (1960–2015) and the projected period (2016–2040).

Weather index insurance

For the purpose of insurance, an elementary weather index contact pays an indemnity according to the following schedule (Vedenov and Barnett, 2004)

$$f(i|x, i^*, \lambda) = x \times \begin{cases} 0, \text{if } i > i^* \\ \dfrac{i^* - i}{i^* - \lambda i^*} \text{if } \lambda i^* < i \leq i^* \\ 1, \text{if } i \leq \lambda i^* \end{cases}$$

The elementary contract pays out when the index i falls below the trigger (also called strike) i^* with the indemnity proportional to the difference between the index and the trigger. The maximum payout occurs when the index falls below the limit λi^*, whereas $0 \leq \lambda \leq 1$. Different methods are available to determine the trigger and generally include (1) realizations of a weather parameter at a certain quantile (e.g. 70%) from the historical climate data or through modelled distributions (El Benni *et al.*, 2016), (2) a given standard deviation (e.g. 50%) above/below the mean weather variable from the historical climate data or (3) determined through polynomial regressions in function of the crop yield (Chen *et al.*, 2017). In practice, several iterations take place from the first setting of the trigger to the final definition and are often driven by the resulting premium amount and the affordability of the insurance buyer. Typically, the sum insured is calculated as either the product of average or projected yield and commodity prices or the product of production cost (includes input supplies, labour and equipment) and commodity prices.

Depending on the weather index and the length of the underlying time series, insurance pricing is typically based on (1) the Expected Loss Calculation (ELC) where a probability density function is applied to the de-trended residuals of the underlying weather variables which forms the basis of risk rates or (2) the Historical Burn Rate (HBR) where risk rates are directly calculated from the historical climate data. The HBR method is more commonly applied and establishes a burning cost that results from aggregated losses and corresponding exposure over a given time and can include prior adjustments for deductible, franchises and limits, development factors for incurred but not reported losses and/or large losses and catastrophe loadings (Parodi, 2015). While relatively simple in its application, HBR has several shortcomings for weather index insurance in that (1) long and consistent weather data are required, (2) large and catastrophe type of losses are only considered as far as they are contained in the data and (3) the development of trends in the frequency and severity of losses cannot specifically be addressed.

In this study, the parameters of the weather index structure, shown in the example of wet season rice and a six-month SPI (SPI6), are determined as follows:

(1) Sum insured: based on a farm gate rice price of US$300/ton, the cost of production is estimated at US$100/ton and represents about a third of the farm gate value. The total sum insured is obtained by multiplying the 2015 wet season production (5.2m tons) with the production costs (US$100/ton) and results in US$520.16m.

(2) Trigger: the average wet season rice production reached 4.533m tons (2006–2015) with a standard deviation of 537,000 tons (12%). The trigger, as the threshold below which a payout occurs, is set to be the double of the standard deviation or

approximately 1m tons. The wet season rice production statistics (2006–2015) reveal the largest shortfalls with 880,000 tons (2014) with a corresponding SPI6 of −5.63 and 865,000 tons (2007) with an SPI6 of −5.53. To cover these two events, the trigger is set as an SPI6 of −5.

(3) Limit: the lowest SPI6 in Central Java from the historical climate data (1960–2015) occurred in 1994 (SPI6 −9.95), followed by 1976 (−9.89) and 1982 (−9.25), while the severe drought years in Indonesia in 1997 and 2014 produced an SPI6 of −8.15 and −5.63, respectively. The lowest SPI6 of the projected period from the RCM is −13.32 (2028) and is significantly higher than in the historical period. To allow for compensation in exceptionally severe drought events, the limit is established at an SPI6 of −15.

(4) Maximum payout: using the assumed maximum shortfall of 1m tons for the wet season at an indemnity of US$100/ton, the maximum payout is set at US$100m.

(5) Payout function: for simplicity, the payout modality is defined to be linear with a payout of US$10m per 1 SPI6 and is obtained by dividing the maximum payout (US$100m) by the difference of the limit (SPI6 –15) and the trigger (SPI6 –5).

Given the 81-year long time series (1960–2040) available for this study, the pricing of the weather index relies on the HBR. The pure risk rate is computed in dividing the total payout obtained by the HBR method by the sum of the maximum payouts over the same time. Subsequently, the pure risk premium is obtained by multiplying the pure risk rate with the total sum insured.

Results

The results of this study provide valuable insights into temporal and spatial rainfall distributions in the province of Central Java, past drought occurrence and rice production shortfalls as well as future drought risk. This study is one of the first to use RCM outputs and to incorporate future drought risk into the development and pricing of weather index insurance.

Drought indices and rice production shortfall

In the province of Central Java, most rice is produced during the wet season (47% of the annual production), while dry season 1 contributes on average 38% and dry season 2 an average of 15% of the annual rice production (2006–2015). While rice production in all three seasons has been increasing since 2006, severe shortfalls occur in 2007 and 2014, which are well-known drought years in Indonesia (Figure 1). The wet season and dry season 1 production shows higher volatility compared to dry season 2 (Figure 1). Seasonal rainfall amounts (1986–2014) are unevenly distributed in that the wet season obtains on average 53% of the annual rainfall while dry season 1 receives 13% and dry season 2 the remaining 34% of the annual rainfall (Figure 1). Wet season rainfall amounts correlate higher with dry season 2 rainfall (r = 0.33) than with precipitation of dry season 1 (r = 0.24), while it correlates most with annual rainfall (r = 0.62). As the main aspect that leads to the onset of drought in Java is a delay of the usual rainfall regime in the wet season (November–March), this leads to severe rice production shortfalls.

Comparison of the drought indices

The SPI shows a good correspondence with SPEI for all investigated time spans of the historical period. A correlation coefficient of 0.973 (p-value<0.05) is obtained between SPI6 and SPEI6 (Figure 2) and 0.970 (p-value<0.05) between SPI12 and SPEI12. Both SPI and SPEI reveal severe rainfall deficits in the historical period including the well-known drought years of 1976, 1982, 1991, 1997, 2002 and 2014 (Figure 2). The droughts of 1991 and 1997 have also been noticed in Sudibyakto *et al.* (2016) through an analysis of SPIs from rainfall data of 31 weather stations on Java island (1985–2004). Among others, Pratiwi *et al.* (2018) noted severe droughts in Java in 1988, 1991, 1997 and 2015 and their relation to the occurrence of El Niño. Due to its simplicity and the higher familiarity of government entities in Indonesia with SPI rather than SPEI, SPI is used in this study as the meteorological drought index.

Analyses of SPI6 and SPI12 for the historical period show a good correspondence with annual precipitation amounts, particularly in years with drought occurrence (SPI < –5) and excessive rainfall events (SPI >+5) (Figure 2). Correlation coefficients between SPI6 and the corresponding rainfall reach 0.87 (p-value<0.05) and 0.46 (p-value<0.05) between SPI12 and annual precipitation.

Drought severity increases in the projected period with the highest negative projected SPI6 of −13.3 (2028) compared to the historical period with a maximum of SPI6 of −9.95 (1994) (Figure 3). While years of consecutive droughts have occurred in the past, for example, 1961–1964 (SPI6 of −7.7, −0.6, −7.3 and −0.9), future years of continuous drought are likely to be more severe based on the RCM output, for example, 2027–2030 (SPI6 −7.9, −13.3, −10.5 and −2.17) (Figure 3). The frequency of severe droughts is likely to decrease in the next 25 years (2016–2040) with four events with SPI6 <–5 (i.e. one such event every 6.3 years) compared to the past 56 years of the historical period with one event of SPI6 <–5 in 3.1 years. Overall, the volatility, expressed as the coefficient of variation (CV) in the SPI6 time series, significantly increases in the projected 25 years (CV of 74.0) compared to the last 25 years of

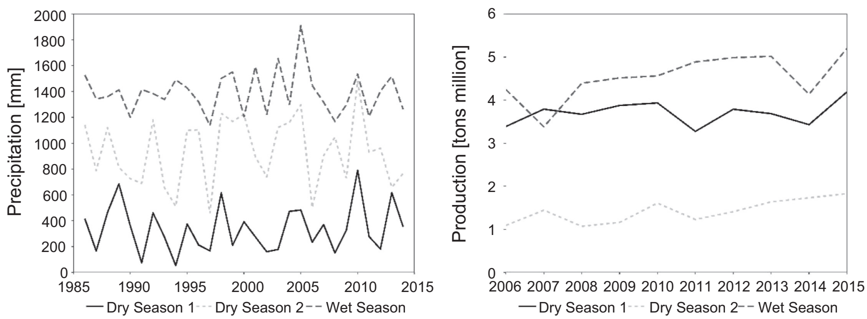

Figure 1.
Left: CRU seasonal rainfall in Central Java for three rice seasons, 1986–2014. Right: Seasonal rice production in Central Java for three rice seasons, 2006–2015

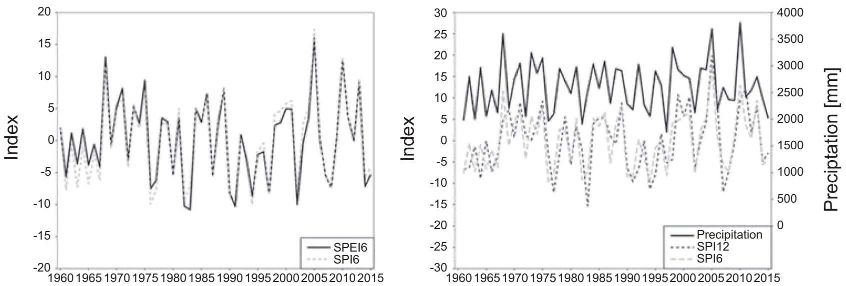

Figure 2.
Left: SPI6 and SPEI6 in Central Java, 1960–2015. Right: SPI6, SPI12 (left axis) and annual precipitation (right axis) in Central Java, 1960–2015. Note that negative values in the SPIs reveal dry conditions (deficit rainfall) while positive values show wet conditions (excess rainfall)

the historical period (CV of 14.9) and reflects that meteorological droughts are likely to be more severe. Positive projected SPIs that indicate excessive rainfall events are 1) comparable in magnitude in the future climate (maximum SPI6 +18.3) with the historical period (maximum SPI6 +17.4) and 2) slightly decrease in frequency with four events with SPI6 >+5 in the next 25 years (or one event in 6.25 years) compared to 13 events in the last 56 years (or one event every 4.3 years) (Figure 3). The finding that drought severity increases in Central Java agrees with the results of Pratiwi *et al.* (2018) where drought indices based on GCM-derived SPIs (2020–2045) are compared to the base-line climate (1986–2017).

Comparison of SPI with rice production

The comparison between SPI12 and annual rice production generates a correlation coefficient of 0.13 (Table 1), which is expected as rainfall is unevenly distributed over the year with the wet season alone receiving on average 53% of the annual rainfall. SPI6 and wet season rice production correlate with 0.71 (Table 1), which can be explained by the fact that the wet season contributes on average 47% to the annual rice production in Central Java and SPI6 captures the main rainfall during the wet season. Rainfall deficits in 2007 (SPI6 –5.5) and 2014 (SPI6 –5.6) have resulted in a wet season rice production of 3.381m tons (2007) and 4.134m tons (2014) and are below the average production of 4.533m tons (2006–2015). Only the wet season rice production correlates significantly with SPI6, while the other seasons do not strongly depend on rainfall as shown through low correlation coefficients with SPI6 and SPI12 (Table 1). The dependence of the wet season rice production on rainfall indicates that the irrigation scheme in the coastal areas of Central Java becomes inefficient in drought years and must be the result of a lack of groundwater and surface run-off. The fact that wet season rice (planting in January and harvest in April) is exposed to drought in Central Java has been noticed in Surmaini *et al.* (2015), where a rice drought impact index that reveals the ratio of drought-induced damaged area to the total planted area shows a high vulnerability to crop damage by drought during March–May and June–August. The difference of the finding of

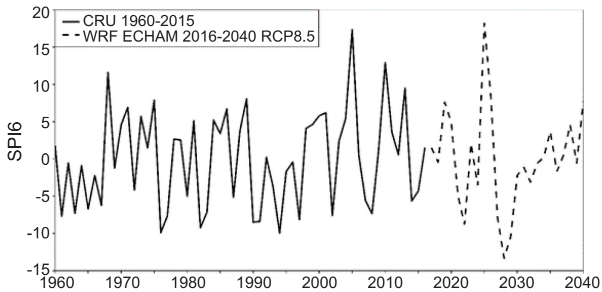

Figure 3. SPI6 based on CRU rainfall for the historical period (solid line, 1960–2015) and SPI6 based on the WRF-RCM (ECHAM RCP8.5) for the projected period (dotted line, 2016–2040)

Table 1. Correlation coefficients between rice production and SPI6 and SPI12 for Central Java, Indonesia, for three seasons (2006–2015) and for all seasons (1986–2015)

Rice season	Correlation coefficient SPI6	Correlation coefficient SPI12
Wet Season	+0.717[a]	+0.497
Dry Season 1	+0.170	−0.314
Dry Season 2	+0.173	+0.185
All Seasons	+0.158	+0.138

Note(s): [a]significant correlation (p-value<0.05)

Surmaini *et al.* (2015) with this study is that drought is parametrized through rainfall deficit (i.e. SPI) in this study and that it takes time for the rice crop to reveal the damage, which Surmaini *et al.* (2015) noticed at harvest times.

Weather index insurance

Based on the correlation analyses of SPI and SPEI and the three rice growing seasons, the best suited weather index covers the wet season as it produces most rice and correlates best with SPI6 and SPI12 (Table 1). The weather index for the wet season is defined through a total sum insured of US$520.16m, a trigger of SPI6 < -5, a limit of SPI6 –15, a maximum payout of US$100m and a linear payout function with a value of US$10m per SPI6.

The weather index generates a payout in 18 out of 56 years for the historical period ranging from US$50,000 (1980, SPI6 –5.005) to US$49.5m (1994, SPI6 –9.950) with an annual average payout of US$7.698m (Figure 4). For the projected period, indemnities occur in four out of 25 years with a minimum of US$29.0m (2027, SPI6 –7.901), a maximum of US$83.3m (2028, SPI6 –13.328) and a yearly average of US$8.199m (Figure 4). While the payout frequency is likely to decrease in the future climate compared to the historical period (Table 2), higher payouts, both in nominal value and in the annual average, are expected due to the increasing drought severity (SPI6 < -5). The payout of the combined period (1960–2040) amounts to US$636m with US$431m from the historical and US$205m from the projected period (Table 2). The correlation coefficient between SPI6 values and payouts reaches -0.71 for the historical period, -0.67 for the projected period and -0.68 for the combined period (Table 2). The negative correlation coefficients reveal that the lower the SPI6 (i.e. the higher the rainfall deficit), the higher the monetary payout under the weather index. The pure risk premium rate that is calculated through the HBR method is obtained as 1.48% for the historical period, 1.58% for the projected period and 1.51% for the combined period, equivalent to an annual risk premium of US$7.85m (Table 2).

As insurance covers future risk, but future risk is in most applications difficult to quantify, insurance pricing typically relies on past losses and loss proxies that are standardized to reflect current insurance terms. However, as climatological hazards including droughts are likely to increase in severity and/or frequency in many parts of the world under climate change scenarios, a view of the future climate is essential, particularly for the agricultural

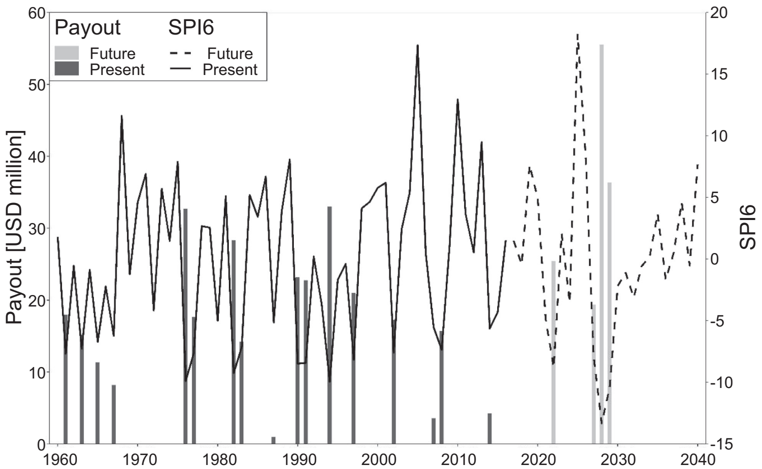

Figure 4.
SPI6 for the historical (solid line, 1960–2015) and the projected period (dotted line, 2016–2040) with payouts of the weather index for the historical period (black columns) and the projected period (grey columns) for wet season rice production in Central Java

sector, which is highly vulnerable to adverse weather conditions. Using RCM-projected climate data, this study offers a unique view into future risk and therefore provides a more robust meteorological drought index that includes future drought risk. Further, RCM projections prolong the time series that forms the basis for index development and therefore limit basis risk in that longer series is more likely to include extreme events.

Conclusions

While index solutions are widely used to transfer natural disaster risks of public infrastructure to (re)insurance and capital markets, only a few applications currently exist for agricultural production assets. One of the key constraints to its wider use is the requirement and difficulty to obtain consistent climate data and loss proxies that are essential to identify and quantify extreme climate events, which will cause high payouts under weather insurance structures. RCM-projected climate data provide the unique ability to access future climate conditions including the frequency and severity of extreme droughts, which is particularly important for agricultural production systems. A better understanding of the future climate and risks will not only enable governments to better prepare for disasters but should also lead to more risk-adequate insurance structures that reflect future risks, which in turn should benefit all stakeholders and the wider society.

Due to its simplicity and its wide use by weather services and in climate research, the SPI is suitable for weather index insurance where rainfall deficit (meteorological drought) is the leading cause of agricultural production shortfalls. As the developed macro-level weather index is based on precipitation deficit on a 0.5° spatial grid, regional drought events should be accurately reflected in the aggregated weather index for Central Java. The methods of this study have been developed for rice production in Central Java; however, they can be applied to other Indonesian provinces that show a clear link between rainfall amounts and agricultural production losses. With adaptations, the concepts can be used in other countries where rainfall deficit alone explains most of the volatility in crop production.

The results of this study can be improved given that (1) historical weather station data are more easily accessible, which will enhance the validation of the CRU climate data; (2) seasonal rice production statistics are available for longer time periods, which will allow more robust correlation analyses with SPIs; and (3) actual disaster assistance spending of the government of Central Java is known and can be correlated to rice production shortfalls and the SPI time series. Although highly computing intensive, RCM-based climate projections beyond 2040 will further improve the understanding of spatial and temporal changes in future drought occurrences and allow the prolongation of the SPI time series beyond the 81 years of this study. Although rainfall deficit (negative SPI6) is the main driver in the wet season rice

	Historical period	Projected period	Combined period
Time Period	1960–2015	2016–2040	1960–2040
Duration (years)	56	25	81
Calculated Min Payout (US$m)	0.05	29.0	0.05
Calculated Max Payout (US$m)	49.5	83.3	83.3
Average Payout (US$m)	7.7	8.2	7.8
Total Payout (US$m)	431.1	204.9	636.1
Pure Risk Premium Rate	1.48%	1.58%	1.51%
Pure Risk Premium (US$m)	7.70	8.20	7.85
Drought Frequency[a] (event/year)	1/6.3	1/3.1	1/3.7
Correlation with Drought	−0.71	−0.67	−0.68

Note(s): [a]Drought is defined through SPI6 of < −5

Table 2. Key parameters of the weather index insurance for different time periods

production, the investigation of excess rainfall events (positive SPI6) could be of interest in Central Java, based on which a weather index that covers drought and excessive rainfall events can be developed.

Generally, the wider access of GCM and RCM outputs will enable the agricultural insurance industry to better understand past extreme events in function of the expectation of such events in future climates.

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Notes

1. The Representative Concentration Pathways (RCP) scenarios 8.5 are available at https://www.ipcc.ch/pdf/assessment-report/ar5/syr/AR5_SYR_FINAL_SPM.pdf (accessed January 2019)
2. The net radiative forcing scenarios are available at http://sedac.ipcc-data.org/ddc/ar5_scenario_process/RCPs.html (accessed January 2019).
3. BMKG issues periodically drought bulletins that are available to government agencies include SPI indices as one of the parameters, e.g. http://mddb.apec.org/Documents/2015/FMP/SEM1/15_fmp_sem1_020.pdf; http://www.droughtmanagement.info/literature/UNW-DPC_NDMP_Country_Report_Indonesia_2014.pdf (accessed August 2018).

References

African Risk Capacity (2019), *Africa RiskView: A Software Package for the Assessment of Impacts of Natural Hazards and Supporting Effective Disaster Response*, African Risk Capacity publication, p. 2.

Allen, R.G., Pereira, L.S., Raes, D. and Smith, M. (1998), "Crop Evapotranspiration: Guidelines for Computing Crop Water Requirements", Vol. 56, FAO Irrigation and Drainage Paper, FAO, Rome, p. 15.

Amien, I., Rejekiningrum, P., Pramudia, A. and Susanti, E. (1996), "Effects of interannual climate variability and climate change on rice yields in Java, Indonesia", *Water, Air, and Soil Pollution*, Vol. 92 Nos 1-2, pp. 29-39.

Barnett, B.J. and Mahul, O. (2007), "Weather index insurance for agriculture and rural areas in lower-income countries", *American Journal of Agricultural Economics*, Vol. 89 No. 5, pp. 1241-1247.

Barrett, C.B., Barnett, B.J., Carter, M.R., Chantarat, S., Hansen, J.W., Mude, A.G., Osgood, D.E., Skees, J.R., Turvey, C.G. and Ward, N. (2009), *Poverty Traps and Climate Risk: Limitations and Opportunities of Index-Based Risk Financing*, IRI Technical Report International Research Institute on Climate and SocietyColumbia University No. 07-02, New York, p. 56.

Berg, E. and Schmitz, B. (2008), "Weather-based instruments in the context of whole-farm risk management", *Agricultural Finance Review*, Vol. 68 No. 1, pp. 119-133.

Berrisford, P., Dee, D., Poli, P., Brugge, R., Fielding, K., Fuentes, M., Kallberg, P., Kobayashi, S., Uppala, S. and Simmons, A. (2011), *The ERA-Interim Archive, Version 2.0*, in ERA Report Series, ECMWF, Reading UK, Vol. 1, p. 23.

Bhushan, C. and Kumar, V. (2017), *Pradhan Mantri Fasal Bima Yojana: An Assessment*, Centre for Science and Environment, New Delhi, available at: http://admin.indiaenvironmentportal.org.in/files/file/Pradhan-Mantri-Fasal-Bima-Yojana-Report.pdf (accessed December 2018).

Binswanger-Mkhize, H.P. (2012), "Is there too much hype about index-based agricultural insurance?", *Journal of Development Studies*, Vol. 48 No. 2, pp. 187-200.

BNPB (2017), *Financial Note: Year 2017*, Publication of Badan Nasional Penanggulangan Bencana (BNPB), Jakarta.

Bokusheva, R., Kogan, F., Vitkovskaya, I., Conradt, S. and Batyrbayeva, M. (2016), "Satellite-based vegetation health indices as a criteria for insuring against drought-related yield losses", *Agricultural and Forest Meteorology*, Vol. 220, pp. 200-206.

Castañeda-Vera, A., Leffelaar, P.A., Álvaro-Fuentes, J., Cantero-Martínez, C. and Mínguez, M.I. (2015), "Selecting crop models for decision making in wheat insurance", *European Journal of Agronomy*, Vol. 68, pp. 97-116.

Chen, W., Hohl, R. and Tiong, L.K. (2017), "Rainfall index insurance for corn farmers in Shandong based on high-resolution weather and yield data", *Agricultural Finance Review*, Vol. 77 No. 2, pp. 337-354.

Chotamonsak, C., Salathé, E.P. Jr, Kreasuwan, J., Chantara, S. and Siriwitayakorn, K. (2011), "Projected climate change over Southeast Asia simulated using a WRF regional climate model", *Atmospheric Science Letters*, Vol. 12 No. 2, pp. 213-219.

Clarke, D.J., Mahul, O., Rao, K.N. and Verma, N. (2012) "Weather Based Crop Insurance in India", World Bank Policy Research Working Paper 5985, available at: http://documents.worldbank.org/curated/en/693741468269445619/pdf/WPS5985.pdf (accessed January 2019).

D'Arrigo, R. and Smerdon, J.E. (2008), "Tropical climate influences on drought variability over Java, Indonesia", *Geophysical Research Letters*, Vol. 35, p. 5.

Dercon, S., Hill, R.V., Clarke, D., Outes-Leon, I. and Seyoum Taffesse, A. (2014), "Offering rainfall insurance to informal insurance groups: evidence from a field experiment in Ethiopia", *Journal of Development Economics*, Vol. 106 No. 1, pp. 132-143.

Doherty, N.A. and Richter, A. (2002), "Moral hazard, basis risk, and gap insurance", *Journal of Risk and Insurance*, Vol. 69 No. 1, pp. 9-24.

El Benni, N., Finger, R. and Meuwissen, M.P. (2016), "Potential effects of the income stabilisation tool (IST) in Swiss agriculture", *European Review of Agricultural Economics*, Vol. 43 No. 3, pp. 475-502.

FAO (2016), *AQUASTAT Main Database*, Food and Agriculture Organization of the United Nations (FAO), FAO, Rome, available at: http://www.fao.org/nr/water/aquastat/data/query/index.html?lang=en (accessed May 2018).

Fischer, T., Su, B., Luo, Y. and Scholten, T. (2012), "Probability distribution of precipitation extremes for weather index-based insurance in the Zhujiang river basin, South China", *Journal of Hydrometeorology*, Vol. 13 No. 3, pp. 1023-1037.

Giorgi, F. (1995), "Perspectives regional earth system modelling", *Global and Planetary Change*, Vol. 10, pp. 23-42.

Guttman, N.B. (1999), "Accepting the standardized precipitation index: a calculation algorithm", *Journal of American Water Resource Association*, Vol. 35 No. 2, pp. 311-322.

Harris, I.P.D.J., Jones, P.D., Osborn, T.J. and Lister, D.H. (2014), "Updated high-resolution grids of monthly climatic observations-the CRU TS3.10 Dataset", *International Journal of Climatology*, Vol. 34 No. 3, pp. 623-642.

Heim, R.R. (2002), "A review of twentieth-century drought indices used in the United States", *Bulletin of the American Meteorological Society*, Vol. 83 No. 8, pp. 1149-1166.

Hess, U., Wiseman, W. and Robertson, T. (2006), "Ethiopia: Integrated Risk Financing to Protect Livelihoods and Foster Development", Discussion Paper, World Food Programme.

Hohl, R. (2019), *Agricultural Risk Transfer: From Insurance to Reinsurance and Capital Markets*, Wiley & Sons, Oxford, p. 440.

IFPRI (2011), “The Impact of Global Climate Change on the Indonesian Economy”, IFPRI Discussion Paper 01148, IFPR, Washington, DC, p. 40.

IPCC (2007) Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K.B., Tignor, M. and Miller, H.L. (Eds), *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge University Press, Cambridge.

IPCC (2013) Stocker, T.F., Qin, D., Plattner, G.-K., Tignor, M., Allen, S.K., Boschung, J., Nauels, A., Xia, Y., Bex, V. and Midgley, P.M. (Eds), *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge University Press, Cambridge.

Jensen, N.D., Barrett, C.B. and Mude, A.G. (2015), “The favourable impacts of index-based livestock insurance: evaluation results from Ethiopia and Kenya”, *ILRI Research Brief*, Vol. 52, p. 4.

Jiang, Z., Raghavan, S.V., Hur, J., Sun, Y., Liong, S.Y. and Dang, T.V.P. (2019), “Future changes in rice yields over the Mekong River Delta due to climate change-Alarming or alerting?”, *Theoretical and Applied Climatology*, Vol. 137 Nos 1-2, pp. 545-555.

Jones, P.D. and Moberg, A. (2003), “Hemispheric and large-scale surface air temperature variations: an extensive revision and an update to 2001”, *Journal of Climate*, Vol. 16 No. 2, pp. 206-223.

Just, R.E., Calvin, L. and Quiggin, J. (1999), “Adverse selection in crop insurance: actuarial and asymmetric information incentives”, *American Journal of Agricultural Economics*, Vol. 81 No. 4, pp. 834-849.

Lawrimore, J.H., Menne, M.J., Gleason, B.E., Williams, C.N., Wuertz, D.B., Vose, R.S. and Rennie, J. (2011), “An overview of the Global Historical Climatology Network monthly mean temperature data set, version 3”, *Journal of Geophysical Research*, Vol. 116, pp. 1-18.

Leblois, A. and Quirion, P. (2013), “Agricultural Insurances Based on Meteorological Indices: Realizations, Methods and Research Challenges”, *Meteorological Applications*, Vol. 20 No. 1, pp. 1-9.

Linnerooth-Bayer, J. and Hochrainer-Stigler, S. (2015), “Financial instruments for disaster risk management and climate change adaptation”, *Climatic Change*, Vol. 133 No. 1, pp. 85-100.

Liyantono, T., Koshi Yoshida, K. and Kuroda, H. (2012), “The influence of El Niño southern oscillation on agricultural production sustainability in a tropical monsoon region: case study in nganjuk district, East Java, Indonesia”, *Journal of Developments in Sustainable Agriculture*, Vol. 7, pp. 65-74.

McKee, T.B., Doesken, N.J. and Kleist, J. (1993), “The relationship of drought frequency and duration to time scales”, *Proceedings of the 8th Conference on Applied Climatology*, Vol. 17 No. 22, pp. 179-183.

MER (2015), *Climate Change Profile Indonesia*, Netherlands Commission for Environmental Assessment, Dutch Sustainability Unit, Utrecht, p. 21.

Mercosur Group (2016), “Parametric insurance applied to agricultural sector in the region of mercosur”, *13th meeting of the AIDA Climate Change Working Party*, Lima, p. 51.

Miranda, M.J. and Farrin, K. (2012), “Index insurance for developing countries”, *Applied Economic Perspectives and Policy*, Vol. 34 No. 3, pp. 391-427.

Miranda, M.J. and Glauber, J.W. (1997), “Systemic risk, reinsurance, and the failure of crop insurance markets”, *American Journal of Agricultural Economics*, Vol. 79 No. 1, pp. 206-215.

Miranda, M.J. and Gonzalez-Vega, C. (2011), “Systemic risk, index insurance, and optimal management of agricultural loan portfolios in developing countries”, *American Journal of Agricultural Economics*, Vol. 93 No. 2, pp. 399-406.

Mortensen, E. and Block, P. (2018), “ENSO index-based insurance for agricultural protection in Southern Peru”, *Geosciences*, Vol. 8 No. 2, p. 64.

Naylor, R.L., Falcon, W.P., Rochberg, D. and Wada, N. (2001), “Using El Nino/Southern Oscillation climate data to predict rice production in Indonesia”, *Climatic Change*, Vol. 50 No. 3, pp. 255-265.

Naylor, R.L., Battisti, D.S., Vimont, D.J., Falcon, W.P. and Burke, M.B. (2007), "Assessing risks of climate variability and climate change for Indonesian rice agriculture", *Proceedings of the National Academy of Sciences*, Vol. 104 No. 19, pp. 7752-7757.

OECD (2017), *Indonesia, in Agricultural Policy Monitoring and Evaluation 2017*, OECD Publishing, Paris, p. 10.

Parodi, P. (2015), *Pricing in General Insurance*, CRC Press Tayler & Francis, Oxford, p. 594.

Pasaribu, S.M. (2010), "Developing rice farm insurance in Indonesia", *Agriculture and Agricultural Science Procedia*, Vol. 1, pp. 33-41.

Patel, N.R., Chopra, P. and Dadhwal, V.K. (2007), "Analyzing spatial patterns of meteorological drought using standardized precipitation index", *Meteorological Applications*, Vol. 14 No. 4, pp. 329-336.

Pratiwi, N.A.H., Karuniasa, M. and Suroso, D.S.A. (2018), "Exploring historical and projection of drought periods in cirebon regency, Indonesia", *E3S Web of Conferences*, Vol. 68, p. 2007.

Raghavan, V.S., Vu, M.T. and Liong, S.Y. (2016), "Regional climate simulations over Vietnam using the WRF model", *Theoretical and Applied Climatology*, Vol. 126 Nos 1-2, pp. 161-182.

Ramsey, A.F. and Goodwin, B.K. (2019), "Value-at risk and models of dependence in the U.S. Federal crop insurance program", *Journal of Risk and Financial Management*, Vol. 12 No. 2, p. 65.

Ratna, S.B., Ratnam, J.V., Behera, S. and Yamagata, T. (2017), "Validation of the WRF regional climate model over the subregions of Southeast Asia: Climatology and interannual variability", *Climate Research*, Vol. 71, pp. 263-280.

Roumiguié, A., Jacquin, A., Sigel, G., Poilvé, H., Hagolle, O. and Daydé, J. (2015), "Validation of a forage production index (FPI) derived from MODIS fCover time-series using high-resolution satellite imagery: methodology, results and opportunities", *Remote Sensing*, Vol. 7 No. 9, pp. 11525-11550.

Skamarock, W.C., Klemp, J.B., Dudhia, J., Gill, D.O., Barker, D.M., Duda, M.G., Huang, X.Y., Wang, W. and Powers, J.G. (2008), *A Description of the Advanced Research WRF Version 3*, NCAR Tech, Note NCAR/TN-475+STR, p. 113.

Skees, J., Varangis, P., Larson, D. and Siegel, P. (2002), "Can financial markets be tapped to help poor people cope with weather risks?", United Nations University World Institute for Development Economics Research, Helsinki, Discussion Paper No. 2002/23, p. 26.

Smith, V.H. and Goodwin, B.K. (1996), "Crop insurance, moral hazard, and agricultural chemical use", *American Journal of Agricultural Economics*, Vol. 78 No. 2, pp. 428-438.

Sudibyakto, H.A., Gunawan, D., Nurjani, E., Sekaranom, A.B., Pujiastuti, I. and Nurrohmah, H. (2016), "A Projection on Climate Change Impact towards Meteorological Droughts over Java Island, Indonesia", *Indonesia International Conference on Agriculture, Food Science, Natural Resource Management and Environmental Dynamics: The Technology*, p. 4, People and Sustainable Development.

Sun, L., Turvey, C.G. and Jarrow, R.A. (2015), "Designing catastrophic bonds for catastrophic risks in agriculture", *Agricultural Finance Review*, Vol. 75 No. 1, pp. 47-62.

Supari, R.M. and Sopaheluwakan, A. (2016), "Mapping drought risk in Indonesia related to El-Niño hazard", *AIP Conference Proceedings*, Vol. 1730 No. 1, p. 70001.

Surmaini, E., Hadi, T.W., Subagyono, K. and Puspito, N.T. (2015), "Early detection of drought impact on rice paddies in Indonesia by means of Niño 3.4 index", *Theoretical and Applied Climatology*, Vol. 121 Nos 3-4, pp. 669-684.

Swiss, Re (2016), "First parametric insurance programme against risks of natural disaster for farmers in China", available at: https://www.swissre.com/media/news-releases/2016/nr_20160803_chinaparametric.html.

Syroka, J. and Nucifora, A. (2010), "National Drought Insurance for Malawi", Vol. 5169, World Bank Policy Research, Working Paper, Washington DC, p. 22.

Tadesse, M.A., Shiferaw, B.A. and Erenstein, O. (2015), "Weather index insurance for managing drought risk in smallholder agriculture: lessons and policy implications for sub-Saharan Africa", *Agricultural and Food Economics*, Vol. 3 No. 1, p. 21.

Taylor, K.E., Stouffer, R.J. and Meehl, G.A. (2012), "An overview of CMIP5 and the experiment design", *Bulletin of the American Meteorological Society*, Vol. 93 No. 4, pp. 485-498.

Thirumalai, K., Di Nezio, P.N., Okumura, Y. and Deser, C. (2017), "Extreme temperatures in Southeast Asia caused by El Niño and worsened by global warming", *Nature Communications*, Vol. 8, p. 15531.

Turvey, C.G. and Mclaurin, M.K. (2012), "Applicability of the normalized difference vegetation index (NDVI) in index-based crop insurance design", *Weather, Climate, and Society*, Vol. 4 No. 4, pp. 271-284.

Vedenov, D.V. and Barnett, B.J. (2004), "Efficiency of weather derivatives as primary crop insurance instruments", *Journal of Agricultural and Resource Economics*, Vol. 29 No. 3, pp. 387-403.

Vedenov, D.V., Epperson, J.E. and Barnett, B.J. (2006), "Designing catastrophe bonds to securitize systemic risks in agriculture: the case of Georgia cotton", *Journal of Agricultural and Resource Economics*, Vol. 31 No. 2, pp. 318-338.

Vicente-Serrano, S.M., Beguería, S. and López-Moreno, J.I. (2010), "A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index", *Journal of Climate*, Vol. 23 No. 7, pp. 1696-1718.

Vu, T.M., Raghavan, S.V., Liong, S.Y. and Mishra, A.K. (2018), "Uncertainties of gridded precipitation observations in characterizing spatio-temporal drought and wetness over Vietnam", *International Journal of Climatology*, Vol. 38 No. 4, pp. 2067-2081.

Weber, R., Fecke, W., Moeller, I. and Musshoff, O. (2015), "Meso-level weather index insurance: overcoming low risk reduction potential of micro-level approaches", *Agricultural Finance Review*, Vol. 75 No. 1, pp. 31-46.

WMO (2009), *Experts Agree on a Universal Drought Index to Cope with Climate Risks*, Press Release of the World Meteorological Organisation, WMO, No. 872, Geneva, p. 2.

World Bank (2013), *NDVI Pasture Index-Based Insurance for Livestock Producers in Uruguay. Feasibility Study*, World Bank, Washington, DC, p. 161.

Zargar, A., Sadiq, R., Naser, B. and Khan, F.I. (2011), "A review of drought indices", *Environmental Reviews*, Vol. 19, pp. 333-349.

Corresponding author
Roman Hohl can be contacted at: hohlroman@gmail.com