Indonesia

Developing Parametric Insurance for Weather Related Risks for Indonesia

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Acknowledgements

EXECUTIVE SUMMARY

Indonesia is one of the main agriculture producers globally and largely relies on domestic staples for its growing population. Droughts related to the El Nino Southern Oscillation (ENSO) frequently reduce rice production which triggers, in the most severe cases emergency imports of rice. Projections of climate change models for Indonesia point towards increasing temperatures and more extreme distributions of precipitation with more frequent dry and wet periods. Climate change impacts are expected to lead to more volatility in rice production. High government subsidies for input supplies and fertilizer as well as trade tariffs under the current agriculture policy have led to inefficiencies in the rice production system besides stagnating yields.

The Government of Indonesia (GoI) has been focusing on modernizing rice production through improved irrigation infrastructure and early warning systems to better cope with developing droughts and support schemes for rice farmers. In case of severe droughts (e.g., 1983, 1997, 2015), the GoI approved additional budget to alleviate impacts of drought for rice farmers through ad-hoc disaster payments and rice imports through its procurement agency BULOG to assure food security. However, a reallocation of budget takes considerable time and administrative efforts and can cause severe financial constraints to farmers if funds are received late. Governments in other countries have been benefiting from ex-ante insurance risk transfer products and capital market instruments in case of extreme climate events to obtain immediate indemnity, stabilise ad-hoc disaster budgets and lengthy avoid budget reallocation processes. While governments use risk transfer solutions mostly for infrastructure, parametric insurance covers have become increasingly available for agriculture assets including crops, livestock and forestry.

This study investigates the development of a parametric insurance product as an ex ante risk management instrument that relies on regional drought indices and provides province-level payouts to the GoI in case of severe droughts. As a case study, the province of Central Java has been chosen given its importance in rice production and a recent request of the Central Java Government to transfer drought risk. This study uses over 50 years of historical gridded precipitation and temperature data to develop *Standard Precipitation Indices (SPI)* and *Standard Precipitation Evapotranspiration Indices (SPEI)* to quantify drought extents at a resolution of 50 x 50 km. A correlation analysis is undertaken between drought intensity (SPI and SPEI) over different time intervals (12 months, 6 months and 4 months) and annual as well as seasonal rice production including one wet rice season and two dry rice seasons. This study reveals that a 4 months SPI (January-April) and wet season rice production show the highest correspondence, based on which a parametric insurance product has been designed for payouts of droughts at province level (SPI of -5 up to SPI of -20). To validate assumptions of the possible maximum drought intensity, which is necessary to define the payout function of the parametric insurance product, SPI values are used from the last 56 years (1961-2015) of rainfall observations and projections from climate change models for the next 25 years (2016-2040). Following common market practise, the structure of the parametric insurance product is priced following the *Historical Burn Rate* method ~~is used~~. As a first of its kind, the developed drought indices are validated with outputs of a climate change model for Central Java province.

This study has been developed in the context of a wider initiative of the World Bank and IFC on disaster risk financing for the GoI and complements a recently approved IFC Indonesia Agriculture Insurance Project (601736) to develop insurance products at the micro level for farmers and at the meso-level for agribusinesses and lending institutions. Preliminary results of this study have been shown and discussed with the Ministry of Agriculture of Central Java, the National Weather Service of Indonesia (BMKG), the Office of the Insurance Regulator, the Ministry of Finance and leading Indonesian insurers in the form of workshops undertaken in Indonesia (Semarang and Jakarta) in July 2017. The feedback on the concept of the presented parametric insurance solution has been very positive. Further, representatives of the Government of the Central Java province revealed that they have been trying to transfer drought risk for rice production to the insurance market, but no solution could be offered. Additionally, the concept of the parametric insurance product has been discussed with two leading reinsurance companies and a large reinsurance brokerand found strong interest to support this project with reinsurance capacity.

Based on the continued interest from Indonesian stakeholders, a cost-benefit analysis of the parametric insurance product compared to other ex-ante and ex-post risk financing approaches will be undertaken. Further, the availability of longer seasonal rice production data will improve the validation of the developed indices.

CHAPTER 1. Government Disaster Risk Management

Governments have different options to cope with the financial impact of natural disasters, depending on the severity of the disaster, geographical scope and population directly and indirectly affected. Disaster risk financing instruments for governments can generally be classified as i) *ex-post* including tax increases/cess, reallocating funds from other budget items, access to domestic and international credit and borrowing from multilateral finance institutions and ii) *ex-ante* including the building of financial reserves, contingent debt agreements and risk transfer to the reinsurance industry or capital markets, typically through parametric (index) products (see BOX and Figure 1-1).

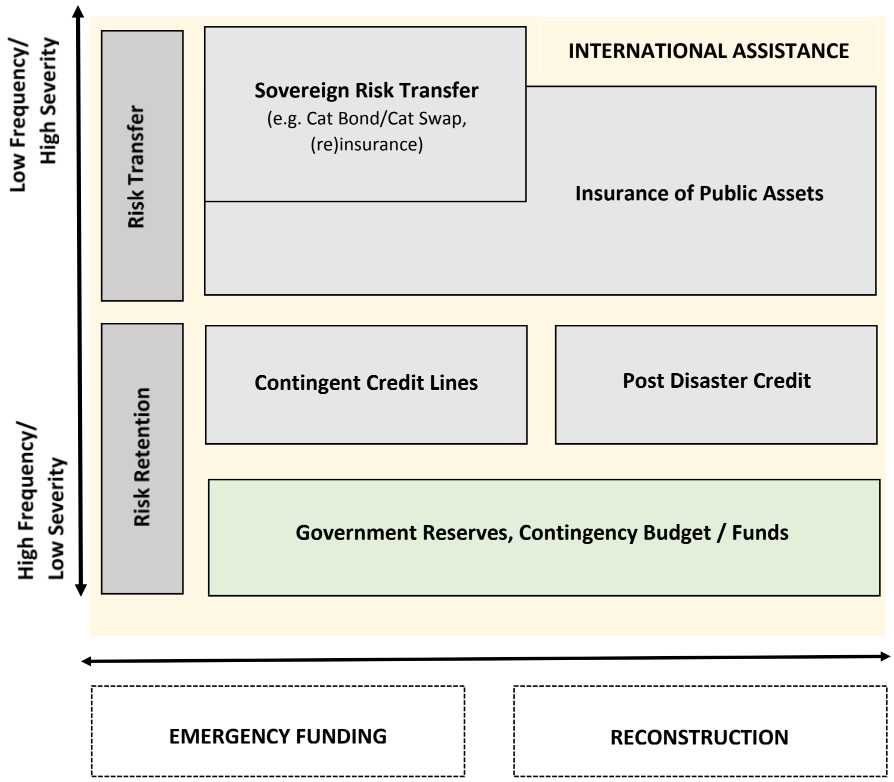

Figure 1-1. Schematic overview government disaster risk management option. Source: Development Solutions for Disaster Risk Finance, GFDRR, World Bank Group.

In the face of the rising frequency and intensity of losses in low- and middle-income countries, the old model of post-disaster financing and reliance on the donor community is increasingly inefficient. Ex-ante financial schemes that are based on optimal *risk-layering* and an efficient disaster risk management framework can provide efficient solutions around immediate liquidity and reconstruction for developing countries. Optimal risk layering contains probabilistic analyses where frequent-low-consequence events and rare catastrophe-type of events are assessed in terms of loss potential to develop disaster risk management strategies for each layer, which is particularly important in the wake of climate change[1]. International financial institutions and the donor community have been promoting proactive disaster risk management systems including catastrophe risk financing models to reduce external assistance based on i) assessing a government's contingent liability to natural disasters, ii) enabling risk transfer to competitive (re)insurance markets and iii) financing sovereign risk.

[1] Linnerooth-Bayer, J. and Hochrainer-Stigler, S., 2015: Financial instruments for disaster risk management and climate change adaptation. *Climatic Change*, 133(1), 85-100.

Depending on the scale and intensity of a natural disaster, a government has budgetary outflows for relief operations, recovery operations and reconstruction and therefore needs liquidity over several months if not years (Figure 1-2).

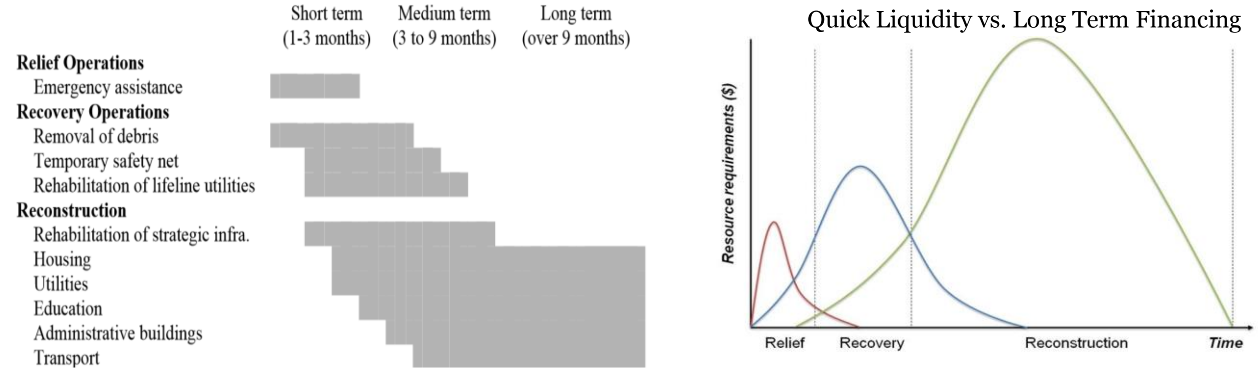

Figure 1-2. Estimated timing of budgetary outflows for a government caused by a catastrophic event. Source: Ghesquiere and Mahul (2007).

BOX: Overview of the Main Disaster Risk Financing Instruments for Governments

Government have a variety of disaster risk financing options to deal with natural disasters in terms of humanitarian aid and reconstruction. While for some low-loss events that occur frequently (low-layer-risk), risk-reduction measures are appropriate, very low probability but high consequence risks (high layer risk), typically need disaster financing strategies which include both, both ex-post (after the disaster) and ex-ante (before the disaster) instruments. Generally, ex-ante instruments are considered as pro-active risk management strategies that provide funding much faster than ex-post approaches to cope with the disaster after occurrence.

Ex-Post Disaster Financing Instruments (see Table 1.1 for details)

- *Budget Reallocation*: allocation of funds to cope with the disaster from other priority development projects take considerable time and often needs parliamentary approval
- *Debt/ Credit*: rising debt and obtaining a credit from domestic and international sources after the occurrence of disaster. While appropriate to finance reconstruction efforts, debts and credits do not provide the required liquidity to finance immediate post-disaster needs and depending on the damage extent. Post-disaster borrowing costs can be significantly higher compared to pre-disaster time and depends on a country's level of indebtedness and ability to service the debt.
- *Donor Assistance*: international donor countries and multilateral financing institutions support certain countries in the aftermaths of a disaster. However, donor funding largely depends on the level of visibility of a disaster in the international media and can take time until funds are available.
- *Tax increases*: provides funds from the public over time to support reconstruction efforts, however can discourage new private investments that are central to redeveloping the economy.

Ex-Ante Disaster Financing Instruments (see Table 1.1 for details)

- *Reserve Fund*: development of a reserve fund achieved through borrowing or accumulating tax revenues to finance immediate post disaster needs.
- *Contingent Debt*[2]: arrange for a contingent credit line to obtain immediate capital after disaster occurrence at terms (interest rate, loan maturity) defined on a pre-loss basis. For disbursement, contingent debt contracts can contain *hard triggers* (debt is only disbursed according to physical

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[2] Clarke, D. and Mahul, O., 2011: Disaster risk financing and contingent debt – A dynamic analysis. World Bank Policy Research Working Paper 5693, Washington DC, USA, 31p.

criteria of the intensity of the disaster) or *soft triggers* (debt is disbursed in case an emergency declarant has been issued by the government).

- *Conventional Risk Transfer:* based on large scale insurance markets with high financial strength that provide coverage for natural disasters for majority of infrastructure or agricultural assets, catastrophe risk can be transferred on an indemnity basis to reinsurance markets. In developed countries, compulsory insurance against natural disasters has shown to be effective, despite some political resistance. In developing countries, insurance markets tend to be underdeveloped and inefficient without or only limited coverage for natural perils, which leaves governments only with the option to transfer risks on an index (parametric) basis to reinsurance and capital markets. The formation of *risk pools* typically facilitates access to reinsurance as an individual country (e.g., Turkish Catastrophe Insurance Pool) or even as a group of countries (e.g., Caribbean Catastrophe Risk Insurance Facility for infrastructure or African Risk Capacity for agriculture).
- *Parametric Transfer*: in the absence of large insurance programs that cover natural disasters, catastrophe risk can be transferred on an index-basis (parametric) to reinsurance and capital markets (insurance-lined securities such as catastrophe bonds) in paying an annual premium to obtain funds in case a disaster occurs of pre-defined intensity. Parametric risk transfer products (unlike some Contingent Credit agreements) are based on *hard triggers* (funds are only paid if the disaster has reached a certain intensity) and are often based on outputs of catastrophe models for the particular disaster event. As based on indices and model results, these products inherently contain basis risk and might not cover all types of natural disasters. The economic theory through the *Arrow-Lind Public Investment Theorem*[3] is usually used as the rationale for countries to apply a risk neutral policy in the evaluation of public investment. However, the assumption of risk neutrality has been challenged when countries are exposed to natural disasters using an alternative model which captures the correlation among individual losses (caused by natural disasters) and the liquidity constraint the government faces[4].

The *Intergovernmental Panel on Climate Change (IPCC)* states that insurance and other financial instruments can play an important role to manage natural disaster risks in the framework of climate change adaptation[5].

In developed countries, losses from natural disasters are typically funded through private risk financing agreements and an efficient public revenue system that relies on taxes. For developing countries, that typically contain low tax ratios and ongoing financial pressures, post disaster funding comes mainly from international donors through multilaterally sourced infrastructure loans and relief aid. In developing countries, the catastrophe insurance and risk transfer markets are clearly underdeveloped, which is demonstrated by the fact that while over 40% of the direct losses from natural disasters are insured in developed countries (usually through compulsory insurance), less than 10% of these losses are covered by insurance programs in middle-income countries and less than 5% in low-income countries[6]. Post-disaster development lending from multilateral financial agencies are important for middle-income countries, while support from bilateral donors is typically more dominant in low-income countries.

Table 1-1 : Disaster Risk Financing and Insurance Options

[3] Arrow, K. and Lind, R.C., 1970: Uncertainty and the evaluation of public decisions. *American Economic Review*, 60(3), 364-378.
[4] Ghesquiere, F. and Mahul, O., 2007: Sovereign natural disaster insurance for developing countries: A paradigm shift in catastrophe risk financing. World Bank Policy Research Working Paper 4345, Washington DC, USA, 26p.
[5] IPCC, 2012: Summary for policymakers. In Fields CB (ed) Managing the risks of extreme events and disasters to advance climate change adaptation. A special report of working groups I and II of the intergovernmental panel on climate change. Cambridge University Press, Cambridge, UK, 1-19.
[6] Cummins, J.D. and Mahul, O., 2009: *Catastrophe risk financing in developing countries: principles for public intervention*. World Bank Publication, Washington DC, USA, 299p.

Reserve Funds	• Funds immediately available for disbursement • Funds still available even if no disaster occurs • Can lower costs relative to insurance given lower payments (covering annual expected loss without any risk buffer or profit load) and lower opportunity costs as funds set aside to meet future disaster costs earn returns • Reduces dependency on debt financing (e.g. for countries concerned about credit ratings) • Can provide a structure for inter-agency coordination and facilitate the earmarking of budget funds on a recurring basis • For markets lacking insurance and disaster risk financing, or where access to such markets is limited for certain economic agents (e.g., households, small businesses), may be the only available ex ante financial tool for these agents	• Opportunity cost of maintaining a liquid reserve • Time delay for the build-up of an appropriate levels of funds to cover disaster risks at initial set-up and following any depletion of funds; less protection compared with insurance during the build-up of funds • May prove more challenging as the level of severity, and expected interval between disaster events, increase; it may be difficult to build up sufficient reserves and, between events, there may be a temptation to use the funds for other purposes
Contingent credit facilities	• Funds immediately available for disbursement • May be more efficient as the scale of disaster risk increases, as it may be more difficult to build up the necessary amount of internal funds to meet the increased expected costs of disasters and since such funds might, in the meantime, be more productively invested elsewhere	• Opportunity costs linked to the holding fee and the return to investors if risk financing is triggered post-disaster • Counterparty credit risk • Access to specialized facilities limited to governments
Insurance	• Immediate, effective transfer of disaster risk; no accumulation of funds needed as in the case of reserves • Provides useful protection against catastrophic disaster events that might otherwise have a material impact on wealth and greatly impede recovery, at a cost that should reflect diversification benefits gained from risk pooling	• Payment may not be immediately available and counterparty credit risk • Opportunity costs of ongoing insurance premiums • In contrast to reserves, funds deployed to manage risk cannot accumulate if a disaster does not occur • Pricing subject to fluctuations in pricing in global insurance markets • May become relatively expensive and possible unviable as the absolute size and level of uncertainty surrounding the occurrence of a risk event increase
Catastrophe -linked securities (including CAT bonds)	• Effective transfer of disaster risk; no accumulation of funds needed as in the case of reserves • In comparison with reinsurance, can provide greater security and rapidity of payment as they are fully backed by collateral and are based on clear, easily verifiable triggers, particularly if a parametric trigger is used • Are less sensitive to potential disruptions in global insurance markets and can provide multi-year coverage	• Opportunity costs of ongoing interest payments (similar to insurance) • May present relatively large fixed costs if bespoke securities are issued • For parametric products, may present basis risk (triggered benefits may not match actual losses) • Potential regulatory barriers for recognition of catastrophe-linked securities as a risk management tool • Investor knowledge and education may be limited, limiting demand • May negatively impact non- or lightly-regulated investors, given limited knowledge of long-tailed risks. Transparency of the risk distribution is important in capital market solutions. • Reinsurance solutions may prove more flexible, competitive
Source: Disaster Risk Assessment and Risk Financing – A G20/OECD Methodological Framework (2012)		

The optimal strategy to finance post-disaster liquidity for a government which has restrictions with budget reallocation and reserve funds, is likely to include risk retention through reserving to cover small losses and contingent credit as well as risk transfer through reinsurance and/or capital markets. While frequently used by governments or a group of governments to transfer risk to the (re)insurance industry and capital markets[7], such solutions in the form of insurance or financial instruments (derivatives) are

[7] For an overview of risk transfer products for governments, see ….

becoming increasingly available for agriculture assets. The following discusses three examples how government use ex-ante risk transfer for agriculture risks in the form of catastrophe risk insurance.

Crop and Livestock Disaster Insurance in Mexico (CADENA)

The Government of Mexico is addressing weather related catastrophes through the CADENA[8] program. CADENA was launched in 2003 under the Ministry of Agriculture, Livestock, and Fisheries (SAGARPA), the Mexican Government (both Federal and State level) and has been providing insurance protection against catastrophic risks to its smallholder farmers via both parametric and indemnity-based insurance, involving public and private insurance/reinsurance companies to underwrite the risks. Since its inception, CADENA has grown to cover most of Mexico's states with over 70% of the 14 million hectares of agricultural land cultivated annually by smallholders. In 2012, CADANA covered a total sum insured of US$ 675 million with the Federal government budget for this program at US$ 232 million[9]. CADENA covers both crops and livestock through i) insurance for catastrophic events (Seguro Catastrófico) and ii) ex-post direct financial support (Apoyos Directos) to agricultural producers affected by natural calamities. Seguro Catastrófico is a macro-level agricultural insurance product purchased by the Federal and/or State governments and provides payouts to the Federal and/or the State government (the policyholders) in the occurrence of a covered event. The Federal and/or State government in turn provides assistance to farmers in the form of a pre-agreed lump sum per farm. CADENA buys catastrophe risk protection from the international reinsurance market.

Seguro Catastrófico includes four products of which two are based on parametric triggers in i) a macro-level *Parametric Crop Weather Index Insurance* (Seguro Agrícola de Índices Climáticos, or SAIC) which uses weather stations to insure crops against key perils such as rainfall deficit (drought) or excess rain (floods) and low temperature (freeze) for maize, beans, sorghum and barley, and ii) a macro-level *Livestock-Pasture Normalized Difference Vegetation Index* (NDVI) insurance to cover shortfalls in grassland production (Seguro Pecuario de Índices de Vegetación, or SPIV) to protect livestock producers to feed their livestock resulting from the shortage of pasture lands due to hydro-meteorological shocks. Evidence shows that CADENA has been successful as a tool to reach the most vulnerable farmers in the country. An independent evaluation of the program conducted in 2009 confirmed that more than 90% of surveyed beneficiaries were primarily involved in agricultural crop livestock and fishing activities, and that nearly 70% of crop beneficiaries managed less than 5 hectares of land. Further, 99% of the surveyed beneficiaries reported they had returned to their agricultural activities after a climatic event thanks to the indemnities received from CADENA. However, surveyed beneficiaries (as high as 72% of crop producers) noted that the payouts were inadequate to cover the costs of their investments in their agricultural enterprises, although 97% of respondents advised that all affected farmers in their locality had received assistance from the program [10].

Drought Insurance in Africa (African Risk Capacity)

The African Risk Capacity (ARC) is a region-wide initiative by African countries to address weather related risks ex-ante by creating a risk pool. As a specialized agency of the African Union, ARC helps member states improve capacities to better plan, prepare and respond to extreme weather events and natural disasters with a focus on drought disasters. Initially capitalized by a combination of premiums by member states and donor funds, payouts for droughts quantified through a Water Requirement Satisfaction Index (WRSI). The ARC risk pool exists since 2012 and cover 9 countries for drought risks

[8] CADENA stands for Componente para la Atención a Desastres Naturales en el Sector Agropecuario y Pesquero

[9] World Bank, 2013: CADENA Catastrophe Insurance: A Social Safety Net for Small-scale Farmers in Mexico. Report 88100, Washington DC, 4p.

[10] The World Bank, Latin America and the Caribbean Region, Agriculture and Rural Development, CADENA Catastrophe Insurance: A Social Safety Net for Small-scale Farmers in Mexico, October 2013;

with a total of three payouts been made in the Sahel region when the drought parameter was triggered (USD 27 million, out of USD 197 million coverage)[11].

Analyses by ARC suggests that a widespread catastrophic drought in sub-Saharan Africa today could cost above USD 3 billion in emergency assistance, which would put an unprecedented financial strain on African countries and donor countries' aid budgets. As it was, the response system to natural disasters was not as timely or equitable as it should or could be, with much of the cost borne by farmers. International assistance through the appeals system is typically secured on a largely ad-hoc basis after disaster strikes, and governments are forced to reallocate funds in national budgets from essential development activities to crisis response. Only then can relief be mobilized toward the people who need it most, and often too late. Based on the premise that managing risks in an ex ante fashion is more economical and efficient and additionally saves more lives and livelihoods, the aim of ARC is to catalyse a better risk management system for Africa and provide capacity building support required to implement such a system. As an insurance risk pool, ARC's objective is to capitalize on the natural diversification of weather risk across Africa, allowing countries to manage their risk as a group in a financially efficient manner to respond to probable but uncertain risks.

Members of the ARC risk pool receive a payout when the rainfall deviation is sufficiently severe such that the estimated response costs cross a certain pre-defined threshold/trigger point. When that threshold is crossed, qualifying risk pool members receive a payout within 2 - 4 weeks of the end of the rainfall season, thereby allowing them to begin early intervention programs before vulnerable populations take negative coping actions. The ARC currently offers a maximum coverage of USD 30 million per country per season for drought events that occur with a frequency of 1 in 5 years or less. ARC buys reinsurance protection from the international market to cover catastrophe risks for its risk pools.

ENSO Catastrophe Insurance in Peru

In 2015, the Government of Peru established the *Agricultural Catastrophe Insurance Facility* (Seguro Catastrófico Agropecuario or SAC) with the aim to deal with agriculture-related emergency situations caused by extreme weather events such as El Niño. Peru's farmers have been particularly vulnerable to the flooding/excess rainfall impacts of El Niño. SAC protects 550,000 hectares of crop land in 8 regions with a total sum insured of USD 156 million. It will also cover crop losses due to other weather or climate threats such as severe frost, as well as rainfall. SAC operates under a multi-year (3-years) insurance agreement[12]. The Peruvian government's actions of purchasing catastrophe insurance coverage for an impending El Niño event shows the severity with which the country can be impacted by rainfall during an El Niño year. It is also a good example of the importance of insurance and risk transfer to provide risk capital after severe weather events needed to help the local economy recover.

The international experience with ex-ante risk transfer solutions of governments for agriculture assets has clearly shown the financial benefits compared to the common post disaster coping approaches. The basis of successful macro-level risk transfer products for agriculture are transparent underlying indices, high correlations between the indices and agriculture production and payout functions that have been developed in collaboration with government stakeholders.

[11] Daniel Runde, Forbes Opinion, African Risk Capacity: Insurance For African Development, 22 December 2015; Some numbers taken from ARC CEO panel discussant Simon Young during the Paris 2015 Global Index Insurance Conference, 14 – 15 September 2015

[12] Artemis, Peru buys catastrophe insurance to protect farmers from El Niño losses, September 24, 2015

CHAPTER 2. Overview of Agriculture in Indonesia

Indonesia has the world's 4th largest population and is the 10st largest agricultural producer. At a global scale, Indonesia is the largest palm oil producer, the 2nd largest producer of natural rubber and cacao and the 3rd largest rice producer and consumer after China and India. Agriculture remains a key sector in the national economic development through the contribution of food, industrial raw materials and feed ingredients, the creation of Gross Domestic Product (GDP), foreign exchange earnings, labour absorption and income of rural households. In recent years, agriculture contributed on average 13.5% to Indonesia's GDP and employed 34% of the labour force[13]. The share of export value of agriculture in recent years is around 20% and is dominated by palm oil and rubber, which contribute 60% of the total agro-food exports. Key agriculture products include palm oil, rubber, timber, cocoa, coffee, tea, tobacco, rice, sugarcane, corn, cassava, tropical fruits, spices, poultry and fisheries.

Crop areas are located in i) lowlands (<200 m) and typically include rice, maize cassava, fruit and perennial crops, ii) highlands (>800m) where vegetables and cool-climate crops are grown n iii) meso-level production (200-800 m) dominated by vegetable production. In 2009, around 17% of the crop land is irrigated with half of the irrigation equipment considered to be in good condition.

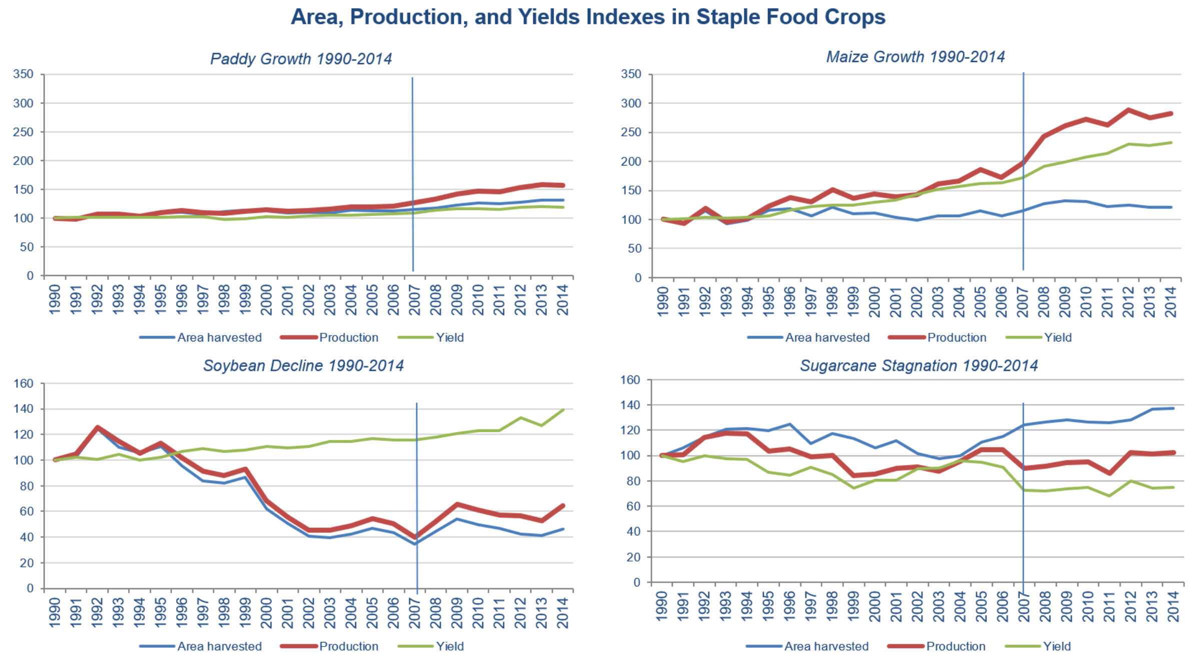

Figure 2-1. Development of area harvested, production and yield for rice (paddy), maize, soybeans and sugarcane for 1990-2014. Source: FAOSTAT/World Bank 2017 (Annex to report on A Modern Food Policy for All Indonesians: Evidence and Strategic Directions.

Agricultural land includes 23.6 million ha of arable land (44%), 19 million permanent crops (35%) and 11 million permanent pastures (21%), with areas of permanent crops (especially palm oil) rapidly expanding[14]. Agricultural production volume has increased by 97% from 1990 to 2009 with an average annual increase of 3.4% over the same time period but with significant fluctuations riven by adverse weather conditions (e.g., the 1997-98 El Nino) and economic turmoil (e.g., Asian crisis) which impacted crop production and to an even higher extent the livestock sector. Agriculture statistics of the period 1990-2014 show that i) rice (paddy) production increased as a result of land expansion and increasing yields (0.8% per year) but at a lower pace than for peer countries, ii) maize production which is mainly

[13] OECD, 2017: Indonesia, in Agricultural Policy Monitoring and Evaluation 2017, OECD Publishing, Paris, 10 p.
[14] FAOSTAT, 2012

used for feed, increased significantly as a result of higher yields, iii) soybean production declined as a result of reduced area and iv) sugarcane production stagnated despite increasing area harvested but as a result of decreasing yields (Figure 2-1). In Indonesia, food crop production is dominated by small scale farms with an average area under production of 0.3-1.4 hectares with little mechanisation. Perennial crops (e.g., palmoil, rubber) are mainly produced by large private- and government-owned farms on average land sizes of 2,600 hectares and nearly occupy 20% of agricultural land. Driven by international demand, output levels of palm oil in 2010 have increased nine-fold since 1990. The livestock sector is dominated by poultry, followed by ruminants (mainly beef cattle, goats and sheep) and remains small and fragmented but with the emergence of larger and more industrialised production sites. Due to the expansion of agriculture, natural resources and the environment are under strong pressure with soil erosion and deforestation as some of the immediate consequences.

BOX: The Importance of Rice

Rice is the main food crop and consists of 19% of the total value of agricultural production (2009) and is grown on over 30% of the total crop area but has been declining over time. Indonesia is largely self-sufficient in rice but occasionally imports rice, particularly when domestic production is impacted by adverse weather conditions. For rice, Indonesia reached self-sufficiency status in the mid-1980s and in 2008-2009 but usually imports on average 3 million tons of rice to maintain a rice stockpile of 1.5-2 million tons. To lower per capita rice consumption, the government introduced the *one day without rice per week* campaign while promoting consumption of other staple foods. At current rice consumption rates, population growth projections and an overall decline of per capita rice consumption, it is estimated that Indonesia will require 38% more rice in 25 years, which must be contributed through an increase in rice yields from the current 4.6 t/ha levels to over 6 t/ha[15]. Rice has a key role in the agricultural policy where subsidies are provided for input supplies, fertilizer and infrastructure and certain trade tariffs are supposed to protect the farmers.

Around 90% of Indonesia's rice production comes from smallholders that operate on farm size of less than 1 hectare, with the majority of farmers cultivating landholdings of 0.1–0.5 hectares. Rice is grown by around 77% of all farmers in the country under predominantly subsistence conditions. The production of rice is concentrated on the islands of Java and Sumatra with Java alone contributing nearly 60% of the total annual production. Rice is cultivated in i) irrigated and well fertilized lowlands production systems and ii) upland systems that are typically rainfed. In most regions, two to three rice crops are produced per year. About 84% of the total rice area was irrigated in 2012 with a predominance of river-based irrigation.

Indonesia's rice sector is highly exposed to droughts and flash floods related to the *El Niño Southern Oscillation (ENSO)*. In El Niño years the lack of rainfall and the occurrence of droughts cause delayed plantings and less area planted, leading to a severe production shortfall, which in turn contribute to higher inflation, increases in poverty, and unless El Niño risks are appropriately mitigated, can have adverse effects on political stability. In La Nina years, excessive rainfall causes flash floods and riverine flooding and impact rice production, predominantly through lower yields. Annual land conversion rates of over 100,000 hectares from rice production areas to non-agricultural usage, reduces the available land for rice production. As a result, growth in rice areas slowed from 2% per year (1960-1998) to below than a 0.1% increase per year (1999-2010).

The continued growth of population leads to a split of already small farm units among family members under traditional inheritance practices and limits the affordability of higher quality input supplies and the intensification of mechanization and needed investment into higher yielding rice cultivars. With small production units, access to credit (or crop loan) is limited but is necessary to increase access to higher

[15] *http://ricepedia.org/index.php/indonesia*

quality input supplies. Often outdated irrigation equipment is perceived as additional challenges for the rice sector to increase production. In the most recent 2015/16 El Nino, drought affected 570,000 ha of the 2015 secondary rice season and damaged 210,000 ha representing 4% and 2% respectively, of the total area planted to rice in 2015.

In 2003, the number of farms reached 24.9 million with over 50% located in Java where 57% of all farms have sizes of 0.5 ha and less. Landless farmers reached 12% in Java and 7% on other parts of Indonesia (2007). The trend towards decreasing farm sizes continued and is accompanied by a more unequal land distribution in general[16].

Domestic investment in the agricultural sector remains low, while international investors are constrained by restrictions in foreign ownership, complicated land rights and inadequate infrastructure (e.g., transport system, irrigation equipment). Bank financing for small scale agriculture operations is low due to the high risk of production failure from unpredictable weather conditions and the demand for higher value collaterals. In 2010, only USD 10.4 billion (5.5% of the total annual loans) were provided for the agricultural sector and only 4.9% of farmers received loans from non-governmental sources. On the other hand, large scale agricultural companies and conglomerates that operate large plantations (e.g., timber, palm oil, rubber) find easy access to funding through banks, foreign investors and capital markets.

Fragmented supply chains, labour shortage at harvest time, poor harvesting equipment and post-harvest storage facilities and poorly maintained rice mills have led to a 5% loss of paddy and a 5% loss of milled rice in 2011, which would translate into a loss of 3.8 million tons and would have been larger than the 2.7million tons of rice imported in 2011[17].

While poverty has significant decreased, still 13% of the population continues to live below the poverty line, with half of the population vulnerable to falling into absolute poverty in the event of a natural disaster or deteriorating economic conditions[18]. Although the average expenditure from food per house hold has declined from 63% (1990) to an estimated 51% (2009) it remains at high level compared to other countries.

Population growth in Indonesia is expected to increase from 242 million (2011) to 264 million (2021) with GDP projected to increase 6-7% annually, resulting in a continued strong demand for agricultural products. In the growing urban areas, dietary diversification occurs rapidly and leads to falling per capita rice consumption but increased consumption of animal products, fruits, vegetables and processed foods. As a result, Indonesia is accelerating imports for grain and oilseeds (wheat and soybeans) that cannot be efficiently produced domestically. Production of palm oil is likely to continue to increase both driven by increased yields and area planted. Rice will remain the key staple food with domestic supply projected to satisfy demand that will increase from 41.5 million tons (2009-2011) to 54 million tons (2012), which is equivalent of 10% of the global rice consumption relative to Indonesia's share of global rice production of 3.4%. Indonesia is projected to remain a net importer of oilseeds, wheat, sugar and beef as well as dairy products. Indonesia-wide, 92% of households including rice farmers, are net buyers of rice and over 87% of poor households buy more rice than they are selling.

Climate change and potential increases in a more extreme distribution of rainfall regimes, i.e., longer dry periods and more flash floods will adversely impact production over time. Under climate change, Indonesia is predicted to experience temperature increases of approximately 0.8°C by 2030 with a high likelihood for the rainy season to end earlier and the length of the rainy season becoming shorter[19]. In

[16] Rusastra, I.W. et al., 2007: Land and Household Economy: Analysis of Agricultural Census 1983-2003. ICASEPS, Bogor.
[17] World Bank, 2017: A Modern Food Policy for All Indonesians: Evidence and Strategic Directions. Annex.
[18] OECD, 2012: OECD Review of Agricultural Policies: Indonesia 2012, OECD Publishing, Paris, 239p.
[19] IFPRI, 2011: The Impact of Global Climate Change on the Indonesian Economy. IFPRI Discussion Paper 01148, 40p.

2015, Indonesia ranked 96th out of 181 countries in the ND-GAIN index[20] with a downward trend. In terms of food sector vulnerability of all countries, Indonesia is at the 118th rank and 121st in adaptive capacity, which means that Indonesia is medium-vulnerable and relatively unready to combat effects of climate change[21]. Climate variability and change are likely to exacerbate many of the disaster risks that Indonesia faces today. During the past four decades, floods, droughts, storms, landslides, and large-scale forest fires have posed the greatest threats to livelihoods, economic growth and environmental sustainability. Climate change is project to negatively impact the Indonesian economy, especially for the agriculture sector (producers and consumers) with decreasing output of rice adversely affecting food security though increased prices for rice. By 2100, climate change impacts in Indonesia are expected to cost 2.5-7% of GDP[22]. Large-scale forest fires are of a particular concern as shown in 2015 by large scale fires that burned over 2.6 million hectares of land (an area of 4.5 times the size of Bali) with costs estimated to at least USD 16.1 billion, equivalent to 1.9% of the 2015 GDP or twice the cost spent for reconstruction after the devastating 2004 Aceh tsunami[23].

Agricultural Policy

On the back of the 1997-98 Asian crisis, the agriculture sector under the main responsibility of the Ministry of Agriculture (MoA), saw a number of reforms including the Indonesian agricultural policy that include four main aspects in achieving i) self-sufficiency in certain commodities (including rice, sugar, soybeans, maize and beef) to assure food security at affordable prices for the population, ii) diversification of production from carbohydrates (rice and hear) towards more animal-based products, fruits and vegetables, iii) competitiveness of agricultural production and value-added processing and iv) increased welfare of farmers through higher incomes while reducing rural poverty[24]. Additionally, import tariffs on agro-food products were lowered and import monopolies, licensing requirements and export restriction on agricultural products been largely removed, except for rice, sugar and beef.

In recent years, food self-sufficiency was the main driver of policy measures and the government has heavily subsided agricultural outputs and inputs, which are often provided through state-owned monopoly producers. Due to administrative complexities, the lack of land titles and the absence of bank accounts for farmers have prevented the use of less distorting forms of government support. Current policy instruments include: i) minimum purchase prices for rice and sugar and BULOG (see Box) acquiring rice through distribution to poor households (RASKIN program) and rice stock at guaranteed prices set by the government, ii) fertilizer subsidies for small farmers (<2 ha), iii) seed subsidies for rice, maize and soybean and seeds in response to natural disasters , iv) credit at low interest from commercial banks and federated farmers' groups, v) income support for farmers affected by natural disasters vi) insurance with premium subsidies for rice and cattle (pilot programs) and vii) free extension services[25]. Additionally, the following services are provided as part of the agricultural policy: i) free irrigation water but costs to be charged to farmers for operating and maintaining water channel systems through water users' associations, ii) research and development, iii) development of local markets and post-harvest storage facilities. Further, a number of trade policy instruments are used to support the farmers[26]. The agricultural policy is further enhanced through the 2012 Food Law which defines core objectives in terms of i) ensuring physical and economic access for the entire population to food which is diverse, safe and

[20] The ND-GAIN Country Index (http://index.gain.org/about/matrix) of the University of Notre Dame summarizes a country's vulnerability to climate change and other global challenges in combination with its readiness to improve resilience.
[21] http://index.gain.org/about/matrix
[22] World Bank, 2014: Indonesia Risk Profile, Washington, DC.
[23] World Bank, 2015: Indonesia Economic Quarterly December. World Bank publication, Washington,
[24] MoA, 2010: Indonesian Agricultural Strategic Plan 2010-14. Ministry of Agriculture (MoA) of Indonesia.
[25] OECD, 2012: OECD Review of Agricultural Policies: Indonesia 2012, 239p. Box 0.2
[26] For a complete overview of policies, see ReSakss, 2014: The Roles of Input Policies in Transforming Agriculture in Indonesia. Working Paper 03, 42p.

nutritious, ii) improving the welfare of farmers, iii) minimizing reliance on imports for core staple foods and iv) achieving overall control of the country's own food circumstances[27].

The level of government support, measured as the producer support estimate as a share of farmers' gross receipts, has average at 9% annually (2006-2010) but has been highly variable ranging from -10% (2008) to +21% (2010), reflects the government's efforts to stabilise domestic prices and manage the interests of farmers and consumers in the context of price volatility in international markets[28]. Government support for agriculture was equivalent to 4.6% of GDP (2015) and was proportionally the highest among OECD countries and peer middle-income countries. However, food self-sufficiency does not necessarily address food security as while import protection benefits domestic producers, rising food costs are born by consumers, which limits the competitiveness of the agricultural sector. Further, import restrictions that are meant to protect, farmers and translate to higher prices has not been observed as farmers have limited market power relative to processors and distributors and lack of access to reliable irrigation and advisory services. Fertilizer subsidies have not reversed the national trend in declining rates of growth in rice yields and while fertilizer prices have decreased globally, the fertiliser subsidy amount in Indonesia has been maintained at unchanged levels [29].

BOX: Role of BULOG

Founded in the 1960's, BULOG is tasked to maintains grain stocks by selling stocks when rice prices are too high and buying from farmers when prices drop below specific levels. Further, BULOG procures rice from the domestic market and oversees the distribution of subsidized rice for poor people (RASKIN/RASTRA programs) while retaining and managing the national rice reserve stock. BULOG buys around 7% of rice production and sells this at a subsidized rate. Food security concerns are most severe in years of domestic shortfall of rice and resulting price increases as poor households spend on average half of the expenditure on food items. The Presidential Instruction (Inpres) no 5/2015 states that rice is to be imported only if domestic production is not sufficient to meet domestic demand and the government's reserve, and/or to maintain the stability of domestic rice prices. In 2016, the realization of RASKIN/RASTRA distribution until the end of 2016 has reached 2,782,326 tons of rice. Meanwhile, for managing the national rice reserve stock (CBP) in 2016, BULOG has distributed 329,420 tons for disaster relief and 31,1764 tons for rice price control.[30]

[27] ibid.
[28] ibid.
[29] World Bank, 2016: Indonesia Economic Quarterly: Pressures easing. 11p.
[30] *http://www.bulog.co.id/pers/37/6018/13/1/2017/Peran-Bulog-Dalam-Usaha-Pengendalian-Harga-Pangan.html*

CHAPTER 3. Impacts of Weather Extremes on Rice Production

Rice production in Indonesia is strongly influenced by annual and inter-annual variations of rainfall driven by the *El Niño Southern Oscillation (ENSO)* and the *Austral-Asia Monsoon*. In four El Niño years between 1973 and 1992, the average annual rainfall reached only around 67% of the 20-year average in two major rice growing areas in Java, causing a yield decline of approximately 50%[31]. Year-to-year changes in sea surface temperature in the Nino 3.4 area in the Pacific were found to explain 69% of the variance in year-to-year changes in September–December rainfall in Java, based on data from 1971-1998[32]. ENSO alone counts for nearly two thirds of the total variation in rice outputs over the last 30 years[33]. During El Nino phases, rice production is impacted by i) delayed rainfall causing rice to be planted later in the monsoon season and ii) delayed planting of the main season wet rice which does not compensate for larger planting areas in the following season, leaving Indonesia with reduced planted areas and shortfalls.

Farmers in irrigated rice production systems (lowland) plant rice in two or three planting seasons per year, whereas those in non-irrigated systems (upland) plant one or two crops per year. The first planting season, (Wet Season rice), usually occurs between November to February. For the 90-120-day growth cycle of wet season rice, cumulative rainfall of 200 mm is required to prepare the ground for planting with an additional 100 mm of rainfall needed during the growing phase[34]. The wet season rice is in many regions the main rice production. Often, the second crop (dry season 1 rice) is planted after the wet season between March and May, and a third crop (dry season 2 rice) is cultivated between June and August, particularly in fields in which there is high availability of water throughout the year. The dry season 2 rice is often planted based on speculations on available water and weather conditions.

El Nino events are known to delay the onset of the monsoon and wet season rice planting by up to two months. Statistical analyses show correlations between the delay in onset and total rainfall for September to December (Wet Season Rice) of -0.94 in West/Central Java and -0.95 in East Java/Bali[35]. It is estimated that a 30-day delay in the onset of rainy season will diminish wet season rice production in West/Central Java and East Java/Bali by about 6.5 and 11.0 %, respectively[36]. Further, 66% of the inter-annual variance in rice plantings and 40% of the inter-annual variance in rice production during the wet season in Java can be explained by annual fluctuations of sea surface temperatures in the Nino 3.4 region as measured 4-8 months in advance[37].

In Java, the strong 1997-1998 El Niño event caused a reduction in rice area of 700,000 hectares and a production loss of 3.2 million tons of rice, which is equivalent to one-fourth of the total rice traded

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[31] 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*, 92, 29-39.
[32] Naylor, R., Falcon, W., Wada, N. and Rochberg, D., 2002: Using El Nino-Southern Oscillation climate data to improve food policy planning in Indoensia. *Bulletin of Indonesian Economic Studies*, 38(1), 75–91.
[33] Naylor, R. L., Falcon W.P., Rochberg, D. and Wada, N., 2001: Using El Niño/Southern Oscillation Climate Data to Predict Rice Production in Indonesia. *Climatic Change* 50, 255–65.
[34] International Rice Research Institute (IRRI), 2007: Water Management.
[35] Naylor, L.N., Battisti, D.S., Vimont, D.J., Falcon, W.P. and Marshall, B.B., 2007: Assessing risks of climate variability and climate change for Indonesian rice agriculture. *Proceedings of the National Academy of Sciences of the United States of America*, 104(19), 7752-57
[36] ibid
[37] Naylor, L.N., Falcon, W., Wada, N. and Rochberg, D., 2002: Using El Nino Southern Oscillation climate data to improve food policy planning in Indonesia. *Bulletin of Indonesian Economic Studies*, 39(1), 75-91.

annually in international markets between 1971 and 1998[38]. A considerable amount of rice is lost in drought years with regional differences (Figure 3-1). About 1 million ha out of 5.14 ha of agriculture land in Java and Sumatera is sensitive to drought and within the last decade, drought affected areas increases from 0.3-1.4% to 3.1-7.8%[39].

Average Rice Production loss due to drought from 1990 – 2013

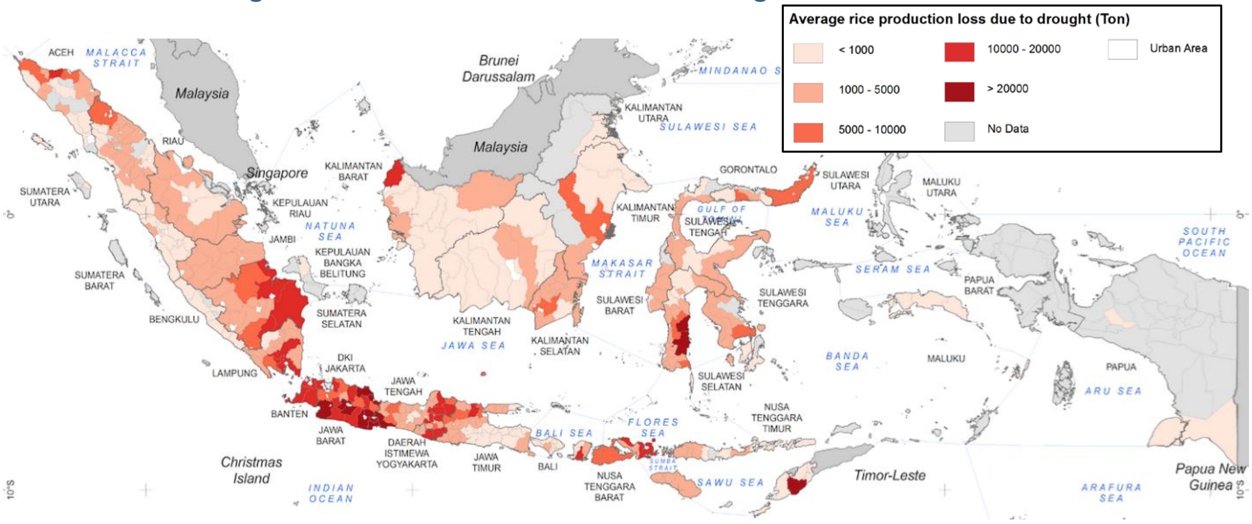


Figure 3-1. Average rice production lost from drought (1990-2013). Source: World Bank 2017 (Annex to report on A Modern Food Policy for All Indonesians: Evidence and Strategic Directions.

Earlier studies on natural disasters have focused on earthquakes, tsunamis and floods impacting major cities[40]. The scale and amount of contingent liability due to extreme weather events like the 1997-98 or 2015-16 El Niño is less understood. So far studies on the impact of El Niño events have focused primarily on household-level impacts on food security and poverty. What is less documented is the significant increases in contingent liability, which includes importing food grains and livestock (beef), increased allocation to social safety programs like RASKIN (the subsidized rice program for low-income families) and PADAT KARYA (employment creation through labour-intensive public works projects), and farm support (additional input subsidy for replanting purposes), among others.

Drought detection and monitoring in Indonesia has been investigated through i) meteorological indices such as the *Standard Precipitation Index (SPI)* and the *Palmer Drought Severity Index (PDSI)*, ii) satellite-derived vegetation health indices such as *Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Vegetation Condition Index (VCI)*[41] and iii) various combinations of i) and ii).

BOX: Monitoring Drought Risk by BMKG

[38] Naylor, R. L., W. P. Falcon, D. Rochberg, and N. Wada, 2001: Using El Niño/Southern Oscillation Climate Data to Predict Rice Production in Indonesia. *Climatic Change* 50, 255–265.

[39] Sembiring, H., Karim Makarim, A., Abdulrachman, S. and Widiarta. N., 2011: Current status of agricultural water management in Indonesia. Indonesian Center for Food Crop Research and Development, Bogor, 16p.

[40] An analytical report on "Indonesia: Advancing a National Disaster Risk Financing Strategy – Options for Consideration", Non-Lending Technical Assistance to the Government of Indonesia in implementing Disaster Risk Financing in Insurance (DRFI),

[41] Shofiyati, R., Takeuchi, W., Sofan, P., Darmawan, S., Awaluddin and Supriatna, W., 2014: Indonesian drought monitoring from space. A report of SAFE activity: Assessment of drought impact on rice production in Indonesia by satellite remote sensing and dissemination with web-GIS. 7th IGRSM International Remote Sensing & GIS Conference and Exhibition. *IOP Conf. Series: Earth and Environmental Science*, 20.

The *Indonesia Agency for Meteorology, Climatology and Geophysics (BMKG)* developed El Nino drought probability maps and tables for all Indonesian provinces, based on global gridded climate data from the Global Precipitation Climatology Centre (GPCC, National Meteorological Service of Germany) and the Climatic Research Unit (CRU, University of East Anglia, UK) which have been analysed for performance with BKMG station data[42]. Operationally, BMKG uses SPI (Figure 3-2) and a Vegetation Health Index (Figure 3-3). BMKG further issues meteorological drought information based on the Standardized Precipitation Index (SPI) method for different time periods. BMKG operates a climate early warning system consisting of drought monitoring and prediction, which are dry season onset, consecutive dry days (CDD, updated every 10 days), and one-month SPI analysis which is received by Ministry of Agriculture, Directorate of Water Resources, Local authorities, and the National Board for Disaster Management[43]. Outputs of the drought monitoring system (particularly rainfall, temperature and SPI) are used for a Fire Danger Rating Index (FDRS) that is used to monitor fire weather conditions for forest areas. The Directorate General of Water Resources issues early warnings on water level heights in dams and reservoirs, which is mainly used for flood planning but also to cope with drought situations.

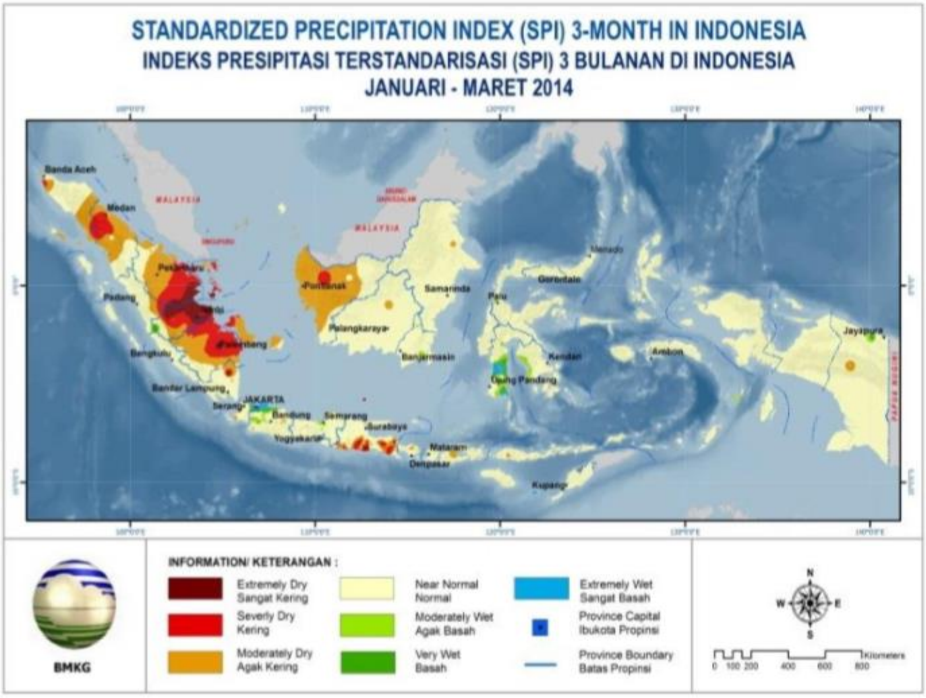


Figure 3-2. Example of a Chart of a Standard Precipitation Index (SPI) produced by BMKG for the time January-March 2014 showing standardized rainfall intensity compared to the long-term climatological in different colors over Indonesia. Source: BMKG.

[42] Supari, Muharsyah, R. and Sopaheluwakan, A., 2016: Mapping drought risk in Indonesia related to El-Nino hazard. AIP Conference Proceedings. 1730(1),

[43] *http://cews.bmkg.go.id/depan.bmkg*

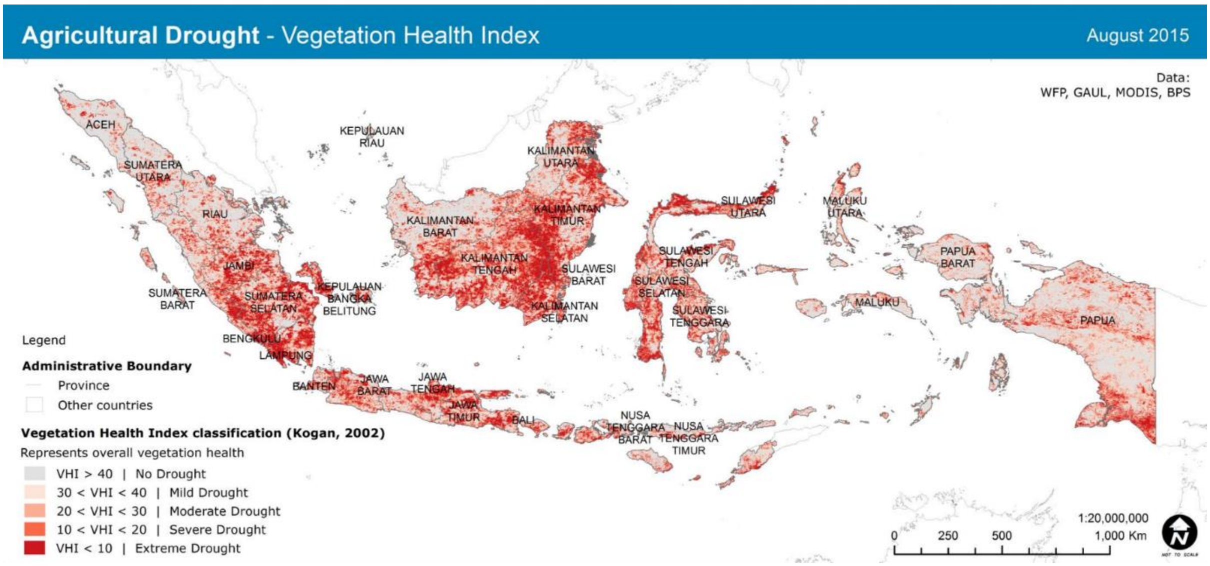
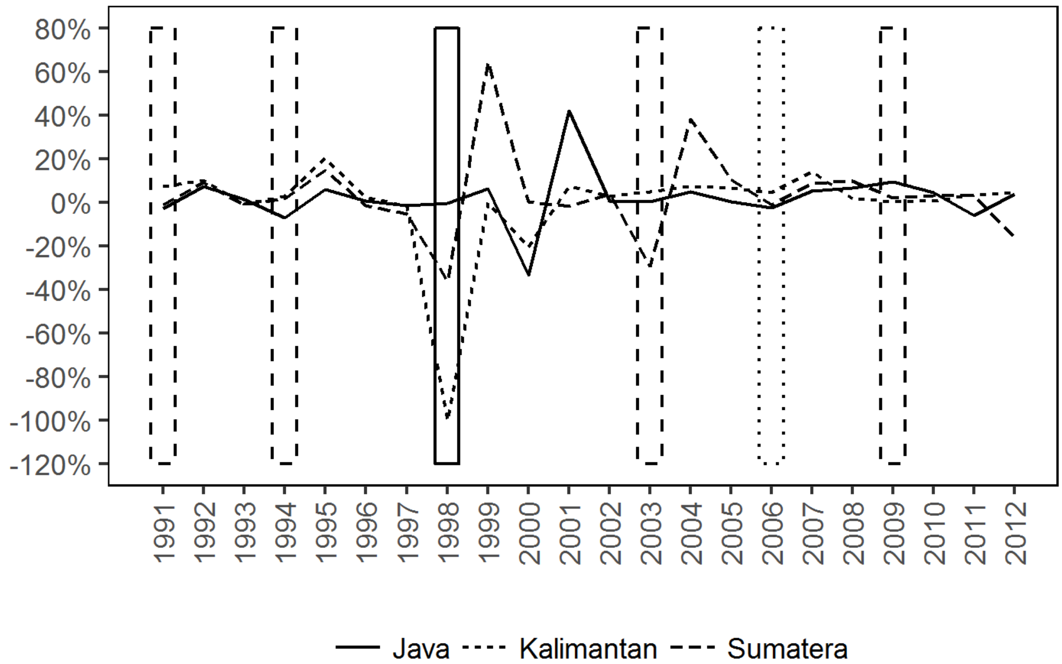


Figure 3-3. Example of a Chart of a Vegetation Health Index (VHI) produced by BMKG for August 2015 showing drought stress in the rice production areas of Indonesia in different shades. Source: BMKG.

Over time, Indonesia has been experiencing strong, moderate and week droughts that are related to El Nino events and a comparison with year-to-year changes in rice production in Sumatera, Java and Kalimantan show large fluctuations in rice production (Figure 3-4). A major part of the volatility in rice production can be explained by drought occurrence that are related to El Nino years. However, it is recognised that Indonesia's official rice production statistics are considered suspect with the methodology used is flawed and when the estimated outcomes have become increasingly politicized, human error and bias becomes systematic[44].



[44] Steven Jaffee, Lead Agricultural Economist at the World Bank, personal communication

Figure 3-4. Strong (solid box), moderate (dashed box) and weak (dotted box) El Nino events and changes in annual rice production relative to the previous year for Sumatera, Java and Kalimantan which are the main producing islands of Indonesia, 1991-2012. Data source: Ministry of Agriculture Indonesia.

The Government of Indonesia (GoI) has taken some actions in coping with drought impacts on agriculture including the provision of drought tolerant seeds, water pumps and advisory for farmers and extension workers on best suited planting times in function of drought forecasts. Besides, several initiatives target of building *embung* ahead of droughts, which are small reservoirs. Further, a forecasting and early warning systems for El Nino-related weather anomalies have been developed for Indonesia and rely on both relatively simple predictive models that are based on changes in sea surface temperatures in El Nino regions in the Pacific[45] and outputs of Global Climate Models.

The use of climate projections from global circulation models has revealed a general warming of temperature and increased volatility in rainfall and a marked increase of in the probability of a 30-day delay in monsoon onset in 2050 with an increase in precipition later in the crop cycle (April-June) by about 10% and a decrease in rainfall of up to 75% in the dry season (July-September)[46]. Experiments have shown that rice yields are sensitive to the rising of minimum temperatures in the dry season; and that yields could decrease 10% for every 1°C increase in minimum temperature[47], posing serious future food security concerns. Projections for Indonesia's rice production reveal possible yield decreases from 4% per year to a total of 16.5% between 2000 and 2080. Climate change affects rice production in various ways including i) each 1°C change in temperature causes lower rice quality and yield losses of 1.3 million metric tons or 10-25% of total production, ii) a 60 cm sea level rise strongly reduces rice yields, e.g. by 300,000 tons in two west Java districts, and iii) a 30 day delay in wet season onset decreases rice yields by 6.5-11%, prolongs the 'hunger season' and may ultimately prevent farmers from planting two consequent rice crops[48].

Table 3-1: Total disaster events in Indonesia 2010-2017

Disaster Event	**Year**								**Grand Total**
	2010	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	
FLOODS	1,008	575	588	716	588	535	849	482	5,341
TORNADOS	395	444	560	501	621	583	687	370	4,161
FIRES	235	492	468	20		3			1,218
LANDSLIDES	398	329	290	296	599	513	626	364	3,415
DROUGHTS	40	221	264	66	7	7			605
FOREST AND LAND FIRES	4	22	51	21	100	44	178	2	422
TIDAL WAVES/ABRASION	12	17	29	36	20	7	23	5	149
EARTHQUAKES	11	9	13	6	14	26	10	9	98
VOLCANIC ERUPTIONS	3	4	7	8	4	12	7		45
Grand Total	**2,106**	**2,113**	**2,270**	**1,670**	**1,953**	**1,730**	**2,380**	**1,232**	**15,454**

45 D'Arrigoa, R. and Wilson, R., 2008: El Nino and Indian Ocean influences on Indonesian drought: implications for forecasting rainfall and crop productivity. *Int. J. Climatol*. 28, 611–616

46 Naylor, L.N., Battisti, D.S., Vimont, D.J., Falcon, W.P. and Marshall, B.B., 2007: Assessing risks of climate variability and climate change for Indonesian rice agriculture. *Proceedings of the National Academy of Sciences of the United States of America*, 104(19), 7752-7757

47 Peng, S., J. Huang, J. E. Sheehy, R. C. Laza, R. M. Visperas, X. Zhong, G. S. Centeno, et al. 2004. Rice Yields Decline with Higher Night Temperature from Global Warming. *Proceedings of the National Academy of Sciences of the United States of America*, 101(27), 9971–9975.

48 MER, 2015: Climate Change Profile Indonesia. Netherlands Commission for Environmental Assessment, 21p.

Source: dibi.bnpb.go.id (processed), 2017

Based on the information from the Indonesia Disaster Information Data (DIBI) of the Indonesian National Board for Disaster Management (BNPB), between 2010 to May 2017 there were 15,454 disaster events on record (Table 3-1). Hydro-meteorological disasters (floods, tornados, landslides, droughts, and forest fires) are the most frequent disaster events, accounting for 90% of the all disaster events. Floods are the most frequent disaster, accounting for 35% of all events (Figure 3-4 and Figure 3-5).

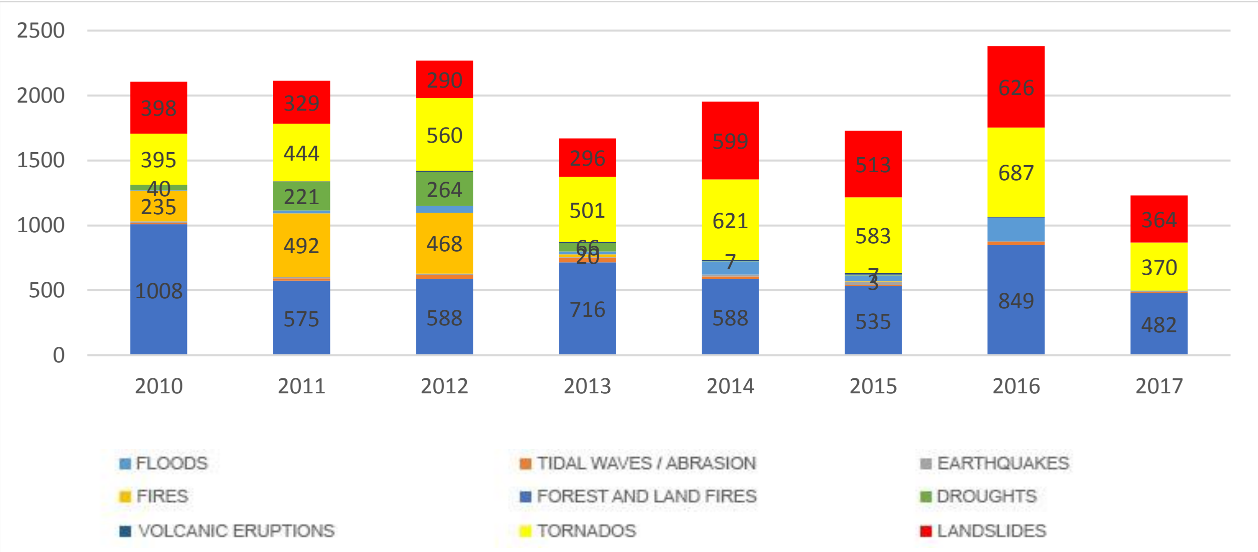


Figure 3-1. Total disaster events in Indonesia 2010-2017. Source: dibi.bnpb.go.id (processed)

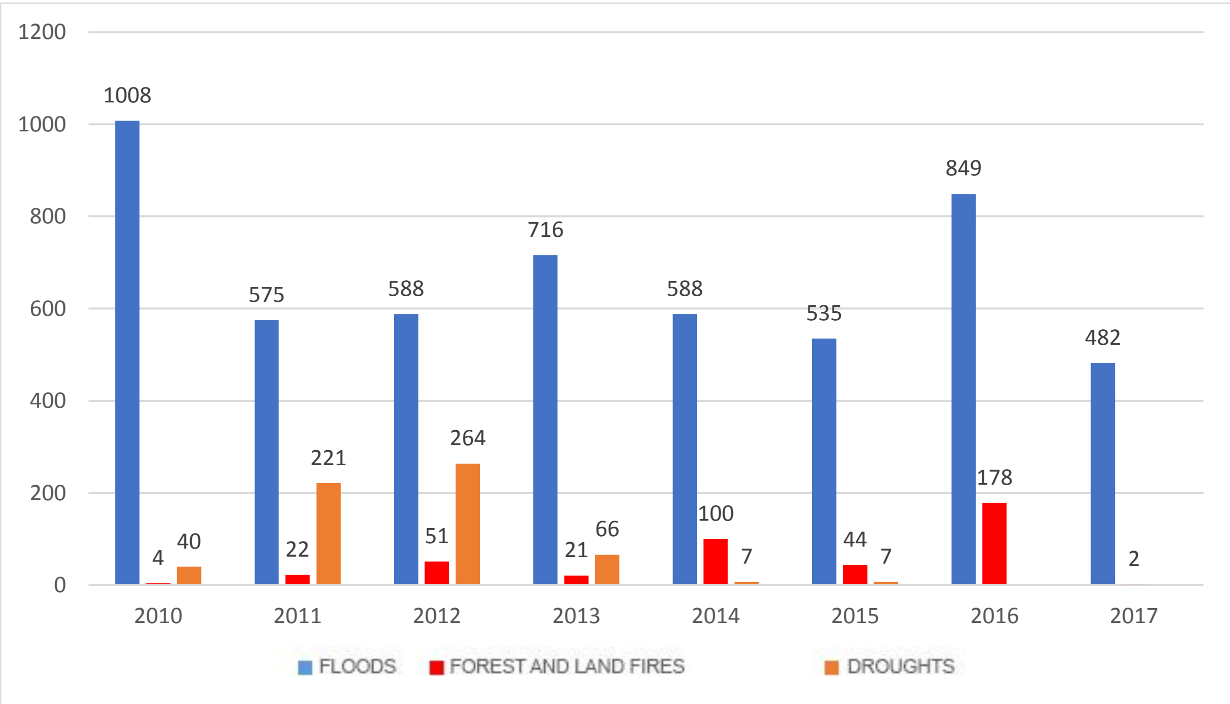


Figure 3-2. Hydro-meteorological Disaster Events, 2010-2017. Source: dibi.bnpb.go.id (processed)

Based on the damage and loss assessment conducted by BNPB, total damage and loss from large disaster events due to climate change and El Nino impacts between 2010 and 2016 reached more than Rp 14.5 Trillion (in excess of USD 1 billion), not including the losses due to forest and land fires in 2015, which is predicted to have been in excess of Rp 220 Trillion (in excess of USD 16 billion).

Table 3-2: Damage and Loss due to Massive Floods, 2010-2017			
No.	**Disaster Event**	**Time of Event**	**Damage & Loss (Rp billion)**
1	Flash Floods in Wasior, West Papua	Sept 2010	280.6
2	Floods in Jabodetabek areas	Jan 2013	8,340.0
3	Flash Floods in North Sulawesi	Jan 2014	1,569.9
4	Flash Floods in Garut	Sept 2016	690.7
5	Floods and Landslides in Sumedang	Sept 2016	134.1
6	Floods in Bandung City	Oct 2016	16.8
7	Flash Floods in Bima	Dec 2016	3,493.3
	Total		**14,525.4**

Source: Ministry of National Development Planning (Bappenas) and Indonesian National Board for Disaster Management (BNPB), updated in 2017

Between 2010 to 2016, the Government of Indonesia on average allocated Rp 4 Trillion (USD 300 million) annually towards reserve funds for disaster management, to be allocated for emergency disaster management as well as post-disaster rehabilitation and reconstruction (Table 3-3). Every year the funds are distributed to regions depending on the disaster impact, and the disbursement of the reserve funds is affected by the intensity of disaster events each year, and is accounted for in accordance with applicable regulations. Climate change related disaster events, including El Nino, accounted for more than 40% of all disbursements from the reserve funds during the period (2010 to 2016).

Table 3-3: Data on Budget Realization of Disaster Management Reserve Funds 2010-2016			
Year	**Budget Allocation (Rp million)**	**Realized Disbursement (Rp million)**	**For Disasters due to Climate Change (Rp million)***
2010	5,312,000.00	5,259,995.00	2,103,998.00
2011	4,300,000.00	4,278,529.00	1,711,411.60
2012	4,000,000.00	1,000,000.00	400,000.00
2013	2,300,000.00	1,697,733.00	679,093.20
2014	3,000,000.00	3,000,000.00	1,200,000.00
2015	4,000,000.00	3,444,045.00	1,377,618.00
2016	4,000,000.00	3,000,000.00	1,200,000.00

Source: BNPB Financial Note, Year 2017
**) Estimated realized disbursement of disaster management reserve funds for disasters such as floods, droughts as well as forest and land fires which amounted to 40% of the total realized disbursement of reserve funds*

In addition, per the tracking of investments towards management and dealing with climate change/el nino impacts, between 2010 to 2017, the GoI allocated budget of Rp 442.6 Trillion (~USD32.8 billion) of which Rp 357.46 Trillion (~USD26.5 billion) was disbursed. The largest allocation is budgeted for subsidies of rice, fertilizers and seeds which amounted to Rp 295.8 Trillion. A significant increase in allocation of funds occurred in 2015 and 2016, Rp 79.1 Trillion in 2015 (or 68% more compared to Rp 47.2 Trillion in 2014), the increase coinciding with the El Nino in 2015 and La Nina in 2016. What is not known is whether such allocation is intended for disaster management of floods or droughts, or forest and land fires.

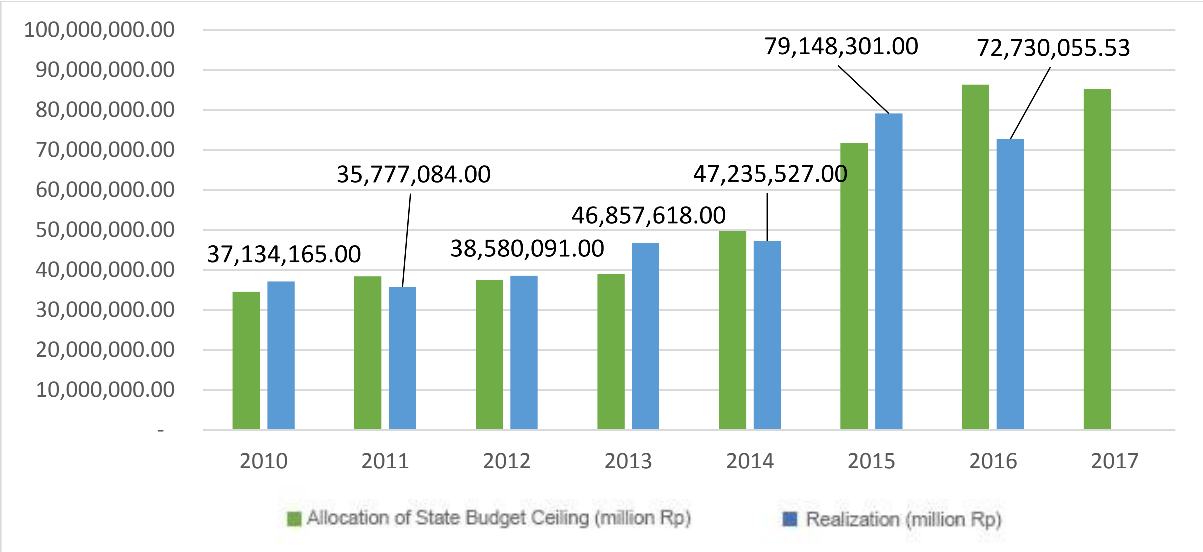


Figure 3-3. Budget Allocation and Realization for management of climate change/El Nino impacts, 2010-2017

CHAPTER 4. Drought Indices for Agriculture

Droughts occur in both high and low rainfall areas and relate to the reduction of rainfall received over a certain area and over an extended period of time. The onset and termination of a drought is driven by factors including high temperature, low relative humidity and the intensity and duration of rainfall including the daily distribution. Since droughts have different impacts on the environment and society, droughts are generally categorised into i) *meteorological drought*, is a lack of precipitation over a region for a period of time relative to average values, ii) *agricultural drought*, is a period with declining soil moisture and resulting crop failure without any reference to surface water, iii) *hydrological drought*, is a period with inadequate surface and subsurface water resources for established water uses for a particular water resource system, and iv) *social-economic drought* relates to failure of water resource systems to meet demands for an economic good water[49]. Droughts occur in a particular order starting with precipitation deficiency (meteorological drought) which impacts soil moisture contents (agricultural drought) and low recharge from the soil to stream and lakes causes low streamflow (hydrological drought) which in severe cases can lead to failures of water resource systems (social-economic drought).

In order to forecast, monitor and plan operations, *drought indices* have been developed reflecting one of several types of impacts, time spans and geographies. Drought indices are quantitative measures that describe drought levels by assimilating data from one or several *indicators* (variables) and over 150 different drought indices have been developed[50]. While some drought indices are used in research and/or for specific applications, some are used as standards to monitor droughts in an operational context. Drought indices can be categorised into i) *meteorological indices*, ii) *agricultural indices*, iii) *hydrological indices*, iv) *remote sensing-based indices* and v) *combined indices* (also called hybrid or aggregated indices) which can include indices of categories i-iv).

Agriculture risk transfer products use drought indices, particularly SPI, SPEI, WRSI, CMI and NDVI, to quantify drought risk and to define indemnity triggers (see Table 4-1 for an overview of common drought indices).

Table 4-1: Common drought indices per type with M = Meteorological Index, A=Agricultural Index, RS = Remote Sensing Index; note that Hydrological Indexes are not listed in this table, Inputs with P = Precipitation, T = Temperature, SM = Soil Moisture, ET = Evapotranspiration, SF = Stream Flow, NIR = Near Infrared and SWIR = Short Wave Infrared.

		Inputs							
Index	**Type**	**P**	**T**	**SM**	**ET**	**SF**	**NIR**	**SWIR**	**Notes**
Percentage of Normal Precipitation (PNC)	M	●							No-standardised index describing rainfall deviation compared to normal but does not allow comparisons of droughts over seasons and regions; needs at least 30 years of data
Deciles of Precipitation (DP)	M	●							No-standardised index dividing rainfall distributions in 10% ranges (deciles)
Standard Precipitation Index (SPI)	M	●							Standardised index transforming rainfall into a

[49] Mishra, A.K. and Singh, V.P., 2010: A review of drought concepts. *Journal of Hydrology*, 391, 202-216.

[50] For a description and discussion of 74 drought indices, see Zargar, A., Sadiq, R., Naser, B. and Khan, F.I., 2011: A review of drought indices. *Environ. Rev.*, 19, 333-349

									normal distribution and expression deficit/excess rainfall in standard deviations compared to long-term normal. Recommend as the main meteorological drought index by the World Meteorology Organisation (WMO)
Standard Precipitation Evapotranspiration Index (SPEI)	M	●	●						Improved SPI index using temperature, water balance and evapotranspiration; in the absence of temporal temperature trends, produces similar results to SPI.
Palmer Drought Severity Index (PDSI)	M	●	●	●			●	●	Index based on soil moisture deficiencies (local available water content) through a water balance model; may not identify droughts as early as the other indices and not well suited for mountainous land or areas of frequent climatic extremes.
Crop Moisture Index (CMI)	A	●	●						Index developed on PDSI to monitor weekly crop development, analyses rainfall and temperature in water balance model.
Soil Moisture Deficit Index (SDMI)	A	●	●	●	●				Uses a crop model and hydrological model at high resolutions and different soil layer and depth; modelled data from a hydrologic model with the Soil Water Assessment Tool (SWAT) are initially used to calculate soil water in the root zone; high complexity.
Water Requirement Satisfaction Index (WRSI) and Geo-spatial WRSI	A	●	●	●	●				Crop specific drought index that uses water balance model and requires additionally soil type and irrigation extent
Normalised Difference Vegetation Index (NDVI)	RS						●	●	Based on visible and near-infrared images, common vegetation health index using near infrared and visible red spectral reflectance
Vegetation Condition Index (VCI)	RS						●	●	Based on thermal images, identifies drought situations and determine the onset, duration and severity of droughts on vegetation; similar to NDVI
US Drought Monitor (SDM)	M/A/RS	●	●	●	●	●	●	●	Composite drought index integrating SPI, PDSI and

									hydrological and vegetation indicators; uses percentile ranking in which indices and indicators from various periods are compared; used mainly in the USA but increasingly considered in other countries
Source: adapted from Zargar, A., Sadiq, R., Naser, B. and Khan, F.I., 2011: A review of drought indices. Environ. Rev., 19, 333-349.									

The choice of a particular drought index to develop risk transfer solutions such as parametric insurance solutions largely depends on the underlying risk, data availability as well as the structure and desired payout function. For risk transfer, a drought index needs to be transparent and to be easily reproduced by risk takers such as reinsurers and capital market participants. One of the most common drought indices to monitor and quantify droughts over different time spans is the *Standard Precipitation Index (SPI)*, which is recommended by the World Meteorological Organisation (WMO) as the most suitable meteorological drought index used for drought monitoring and climate risk management[51].

BOX: Standard Precipitation Index (SPI)

The *Standard Precipitation Index (SPI)* is one of the simplest precipitation-related index that reveals drought and excessive rainfall periods from a purely meteorological point of view. SPI is a probability index that considers only precipitation and is one of the most used indices to determine meteorological droughts. In a first step, the long-term precipitation records are fitted to a Gamma probability distribution function, which, in a second step is transformed into a normal distribution so that the median SPI is zero and with half of the observations being positive (negative) revealing drier (wetter) conditions compared to the median (for details, see **APPENDIX 1**).

The scale of the SPI ranges with a more severe event shown higher values on the index.

Table 4-2 : SPI value classification

SPI Value	**Classification**
>2	Extremely wet
1.5 to 1.99	Very Wet
1.0 to 1.49	Moderately wet
-0.99 to 0.99	Near normal
-1 to -1.49	Moderately dry
-1.5 to -1.99	Severely dry
<-2	Extremely dry

The SPI can be calculated for a variety of time spans and can be used to quantify meteorological droughts. Typically, SPIs are calculated for 1 months, 2 months, 3 months, yearly and multi-year. Although the SPI quantifies a meteorological drought, the fact that soil moisture conditions (which are important for crop growth) respond to precipitation anomalies in a short time, the SPI index can be a valuable proxy for soil moisture content. As SPI is a standardised index, it allows the determination of the rarity of a current drought, the calculation of the probability of the precipitation necessary to end it and the comparison of historical and current droughts between different regions.

[51] WMO, 2009: Experts agree on a universal drought index to cope with climate risks. Press Release of the World Meteorological Organisation (WMO) No.-872, 2p.

CHAPTER 5. Development of Drought Indices for Central Java

Central Java is part of the Java island (Figure 5-1) and is a major rice producer and as other Indonesian provinces is exposed to severe droughts.

Figure 5-1. Map of Indonesia with the location of the Central Java province (insert) and Mapo of the Central Java province. Source: Wikimedia

The government of Central Java has signalled strong interest to a solution to manage rice production shortfalls due to severe droughts. To develop a parametric insurance product, drought indices need to be computed and while there are a large number of possible drought indices available (meteorological and agricultural drought indices), this project uses the Standard Precipitation Index (SPI) and the Standard Precipitation Evapotranspiration Index (SPEI). Both, SPI and SPEI are widely used to quantify meteorological drought risk and the SPI is operationally computed for Indonesia by the National Weather Service (BMKG) to monitor droughts. While SPI only relies on precipitation data, SPEI requires additionally temperature recordings, based on which evapotranspiration is computed. In order to relate the drought indices to actual losses and financial impacts, agriculture production statistics and other loss proxies (e.g., area affected by a natural peril, government ad-hoc disaster spending, economical losses) are needed.

Weather and Rice Production Data

With the increasing availability of high-quality open-source weather data (mostly on gridded format), several datasets are available for Indonesia at different time scales and resolutions (Table 5-1). Additionally, a gridded rainfall and temperature data set recently compiled by the National Weather Service (BMKG) seems to become available soon. Some datasets have shown higher accuracies in tropical and sub-tropical environments. To develop a parametric insurance product, it is essential that weather data are available near real time so that potential losses can be estimated during the period of insurance (i.e., a rice growing season) and computed at the end of the period of insurance to determine the pay-outs. For this project, the following key criteria were applied to select a weather/climate data set: i) long history of weather recordings including rainfall and temperature data, ii) spatial resolution of 50 km or better and iii) known possible biases towards weather station data.

Table 5-1: Overview of open-source gridded weather/climate data							
Name	**Resolution (º)**	**Period**	**Parameter**	**Intervall**	**Area**	**Provider**	**Country**
CRU	0.5	1901-present	P, T	Monthly	Global land	University of East Anglia, UK	UK
CHIRPS	0.25 (0.05)	1981-present	P	Daily	50°S-50°N	University of California, Santa Barbara	USA
UDEL	0.5	1901-2014	P, T	Monthly	Global land	Centre for Climate Research, Department of Geography, University of Delaware. Newark	USA
CPC	0.5	1948-present	P, T	Daily	Global	National Oceanic and Atmospheric Administration	USA
GPCC	0.5	1901-2013	P	Monthly	Global	Deutscher Wetterdienst	Germany
APHRODITE	0.5 (0.25)	1951-2007	P, T	Daily	Asia above 15S land	Japan Meteorological Research Institute	Japan
UW	0.5	1950-2008	P, T	Daily	global land	University of Washington	USA
GPCP	1.0	1996-2015	P	Daily	Global	NASA Goddard Space Flight Centre	USA
TRMM	0.25	1998-2015	P	3 hourly	50S to 50N	NASA Goddard Space Flight Centre	USA
GSMaP	0.1	2001-present	P	Hourly	Asia above 15S land	Japan Meteorological Research Institute	Japan

For this project, the time series of the Climatic Research Unit[52] (CRU) of the University of East Anglia, (UK) are used for rainfall and temperature (CRU series 3.24[53]). CRU data are one of the most widely used datasets in the climate research community and are frequently cited for a variety of applications such as validation of historical records, climate model simulations and climate change studies[54]. These datasets comprise of monthly grids of observed precipitation and temperature for the period 1901-2015 at 0.5° of horizontal spatial resolution, which is approximately 50 km. CRU uses weather station data from different sources including the Global Historical Climatology Network (GHCN) which is an integrated database of climate summaries from land surface stations across the globe[55] and CLIMAT[56]. CRU uses the Angular Distance Weighted (ADW) technique to interpolate precipitation grid cell from the eight nearest weather stations[57]. CRU data have been validated over Southeast Asia and recently the data were used for validation of the regional climate model WRF over Southeast Asia[58] and compared to station based gauge products in Vietnam[59] and attribution of climate change[60]. The CRU dataset is one of the

52 https://crudata.uea.ac.uk/cru/data/hrg/

53 Harris, I., Jones, P.D., Osborn, T.J. and Lister, D.H., 2013: Updated high-resolution grids of monthly climatic observations – the CRU TS3.10 Datset. *Int. J. Climatol.*, 34, 623–642.

54 a list of publications that use CRU data is provided under http://www.cru.uea.ac.uk/publications

55 See https://www.ncdc.noaa.gov.

56 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*, 16(2), 206-223.

57 Willmott, C. J., and Robeson, S. M., 1995: Climatologically aided interpolation (CAI) of terrestrial air temperature. *International Journal of Climatology*, 15(2), 221-229.

58 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*, 71, 263-280.

59 Nguyen-Xuan, T., Ngo-Duc, T., Kamimera, H., Trinh-Tuan, L., Matsumoto, J., Inoue, T., and Phan-Van, T, 2016: The Vietnam Gridded Precipitation (VnGP) Dataset: Construction and Validation. *SOLA*, 12, 291-296.

60 Thirumalai, K., DiNezio, P. N., Okumura, Y., and Deser, C., 2017: Extreme temperatures in Southeast Asia caused by El Niño and worsened by global warming. *Nature Communications*, 8, 15531.

most extensively used data by the climate modelling community and has been used by the National Weather Service of Indonesia (BMKG).

Historical annual rice yield, planted area and production data from 1986 to 2015 in Central Java was collected from the website of Indonesia Ministry of Agriculture[61]. Historical seasonal rice yield, planted area and production was available for Central Java from the Central Java Government for 2006 to 2015. In terms of seasonal rice cultivation and harvest, each year was divided into three season that includes one wet season and two dry seasons, referred to as: *wet season* (January – April), *dry season 1* (May – August) and *dry season 2* (September – December).

Additionally, irrigation extents and soil types were available from Aquastat[62] and World Soil Information (ISRIC)[63] in gridded format and were used in this study to better understand irrigation- and soil-related differences in annual rice yields.

In Central Java, rainfall is unevenly distributed over the three rice growing seasons with the wet season obtaining on average 53% of the annual rainfall, the dry season 1 with 13% and dry season 2 with 34%, based on rainfall data from 1986-2015 (see Figure 5.2). Wet season rainfall amounts correlate higher with dry season 2 rainfall (0.33) than with dry season 1 rainfall (0.24) while it correlates well with annual rainfall (0.62). In Central Java, wet season rice production is the most important as it consists of 47% of the annual rice production, while dry season 1 produces on average 38% and dry season 2 on average 15% of the annual rice production, based on production statistics of 2006-2015 (see Figure 5.1). While rice production has been increasing since 2006 (see Figure 5.2), severe drops in production are noticed in 2014 and 2007, which are well known drought years in Central Java and in Indonesia overall. Further, the wet season and dry season 1 rice production shows more vulnerability to drought, while dry season 2 production is less influenced by drought occurrence (2007 and 2014).

Rice is cultivated in both lowland and upland elevations throughout Indonesia, with the upland crop typically being rain-fed and receiving only low levels of fertilizer applications. Irrigated lowland rice is both well-watered and heavily fertilized, accounting for approximately 80% of total national rice area and 93% of total production.

Water requirement are a function of rice variety and duration ranging from 6,250 m^3/ha of the Mekongga variety (120 day growth cycle) to 4,950 m^3/ha of the Inpari 13 variety (99 day growth cycle) and including water used for crop and land preparation, the requirement increases to 7,909-8,519 m^3/ha and 6,609-7,219 m^3/ha respectively [64]. As a result of irrigation, lowland rice yields on average are about 60% higher than rain-fed upland crop yields. Lowland rice cultivation is heavily concentrated on Java, but is also prevalent on Sumatra and Sulawesi, which contribute about 89% of total national rice production[65].

[61] *http://aplikasi.pertanian.go.id/bdsp/index-e.asp*
[62] *http://www.fao.org/nr/water/aquastat/irrigationmap/index10.stm*
[63] *http://www.isric.org/*
[64] Sembiring, H., Karim Makarim, A., Abdulrachman, S. and Widiarta. N., 2011: Current status of agricultural water management in Indonesia. Indonesian Center for Food Crop Research and Development, Bogor, 16p.
[65] *https://www.pecad.fas.usda.gov/highlights/2016/03/Indonesia/Index.htm*

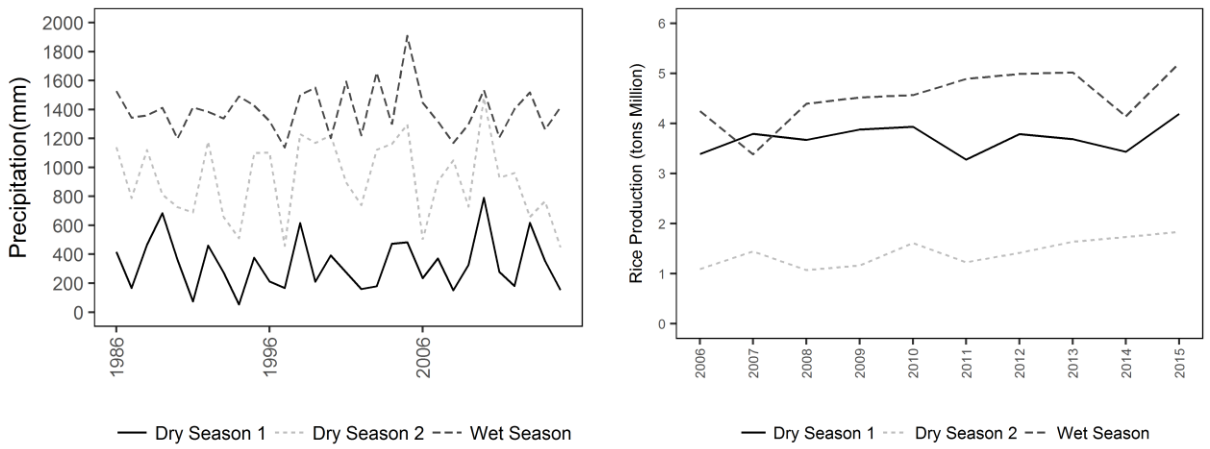


Figure 5-2. Left: Seasonal rainfall in Central Java for the rice cycles of the Wet Season, Dry Season 1 and Dry Season 2 for 1986-2014. Right: Seasonal rice production for the Wet Season, Dry Season 1 and Dry Season 2 for 2006-2015. Data source: CRU for rainfall and Central Java Government for rice production. Data source: CRU rainfall and Ministry of Agriculture Indonesia.

Due to the dominance in production, the efforts of this study focus on wet season rice and the annual rice production.

Methodology

In order to investigate drought impact on rice production, a correlation analysis is undertaken between the drought indices (SPI and SPEI in this study) and wet season as well as annual rice production. The correlation coefficient reveals the extent to which volatility in rice production is driven by rainfall deficit, which is reflected in the drought indices. As the main impact of drought in Java is a delay of the usual rainfall regime in the wet season (November – March) which leads to severe production reductions, rice production appears to be a better proxy than rice yield, as yield only reflects the quantity harvested per surface unit while production includes the quantity harvested over the area planted.

For Central Province, the following steps were taken to correlate drought indices to rice production using a Pearson Correlation:

1. SPI and SPEI values are calculated per month and per grid cell (0.5°, which is approximately 50 km) using the CRU gridded rainfall and temperature data sets
2. SPI and SPEI values are aggregated per grid cell, district and province according to the rice season as i) January to April (4 months) for wet season rice (2006-2015) and ii) January-December (12 months) for annual rice (1960-2015). For brevity, SPI and SPEI with timescales 6 month are referred to as SPI6 and SPEI6, respectively.
3. Seasonal rice production is calculated per district (2006-2015) and annual rice production is computed per district (1986-2015) from the data collected from the Ministry of Agriculture and the Government of Central Java.

Comparison of SPIs of Different Durations

The comparison of the SPI and SPEI (see Figure 5.3) shows a high correspondence with a correlation coefficient between SPI6 and SPEI6 of 0.97 and generate very similar results. Therefore, it was decided to only use SPI as it is i) easier to compute and evaluate by third parties, and ii) used by the National Weather Service of Indonesia (BMKG) for drought monitoring with familiarity of stakeholders in Indonesia. Both SPI and SPEI reveal severe rainfall deficit in the years of 1997, 2002, 2007 and 2014 which were all considered as drought years in Central Java and Indonesia.

Severe drought events happened in Indonesia during dry season period when moderate to strong El Nino occurred such as in the case of 1997. The monthly rainfall distribution of Indonesia for June, July, and August 1997 showed very few rainfall and dry conditions over South Sumatra, Java and Central Kalimantan. In the last 10 years droughts, have occurred in Indonesia, for instance the 2002 drought resulted in dryness in rice field area, up to 350,000-acre farm land suffered for crop loss, and it repeatedly happened in 2007. The 2007 drought event caused over 20,000 acres of paddy field experience crop failure[66].

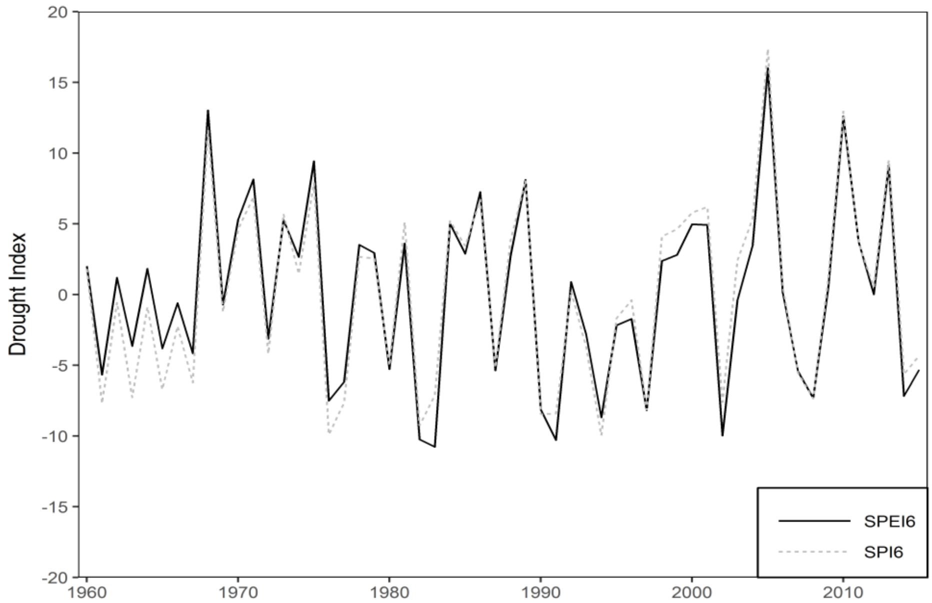


Figure 5-3. SPI6 and SPEI6 for Central Java Province for 1961-2014. Negative values reveal dry conditions (deficit rainfall) while positive values show wet conditions (excess rainfall). Data source: CRU rainfall

Apart from seasonal drought indices from 2006 to 2015 with SPI of 6-month timescale, long-term analyses from 1961 to 2015 with SPI of 4-, 6- and 12-month timescales were carried out (See Figure 5.4). The correlation between SPI4 and precipitation (0.868) is very close to that of SPI6 and precipitation (0.870), and both of them are much higher than the correlation between SPI12 and precipitation (0.46). The three indices show overall consistency, particularly for severe droughts (SPI below -5), while SPI12 appears to show more severe droughts. As observed in other studies[67], as the time period is lengthened to 12, 24 and 48 months, the SPI responds more slowly to precipitation changes, therefore, the period with SPI negative (positive) becomes fewer in number but longer in duration. Thus, it shows more severe droughts.

[66] www.ais.unwater.org/.../597/mod_page/content/79/Indonesia.pdf

[67] McKee, T.B., Doesken, N.J. and Kleist, J. 1993: The relationship of drought frequency and duration to time scales. In: *Proc. 8th Conf. on Appl. Clim. Am. Meteorol. Soc.* Boston, Massachusetts, 179–184.

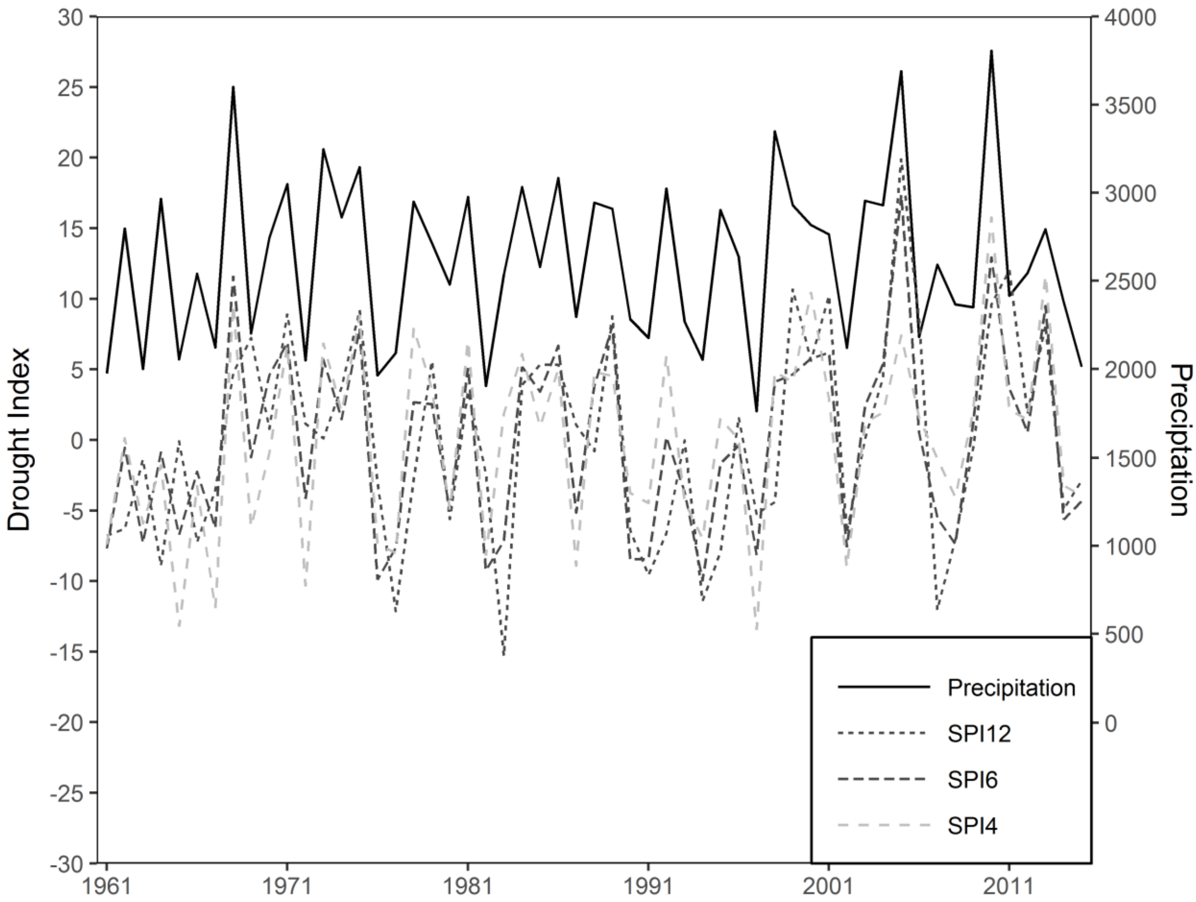


Figure 5-4. SPI4, SPI6, SPI12 and precipitation for Central Java Province for 1961-2014. Negative values of the Drought Index (SPI, left axis) reveal dry conditions (deficit rainfall) while positive values show wet conditions (excess rainfall). Data source: CRU rainfall.

Comparison of SPIs with Rice Production

The comparison between cumulative 12-month SPI6 indices and annual rice production generates a correlation coefficient of 0.16 (Figure 5-5), which is driven by the strong seasonal influence of the rainfall distribution and rice planting patterns, i.e., the wet season alone receives on average 53% of the annual rainfall and in cases of delays (as often triggered by El Nino events), smaller planting occurs in the wet season and higher planting in the following dry seasons. The cumulative 4-month SPI (SPI4) and seasonal rice production correlates to 0.72 (Figure 5-6), which can be explained by the fact that the wet rice season is the dominant production contributing on average 47% of annual rice in Central Java and the SPI4 captures the main rainfall during the wet season. The years of 2007 and 2014 reveal rainfall deficit (drought) and resulted in a lower rice production.

Due to the higher correlation, this study focuses on a risk transfer product for the wet season. While it would be desirable to obtain more data on seasonal rice production than 2006-2015 to evaluate correlations for longer time series, such data were not available in the framework of this study.

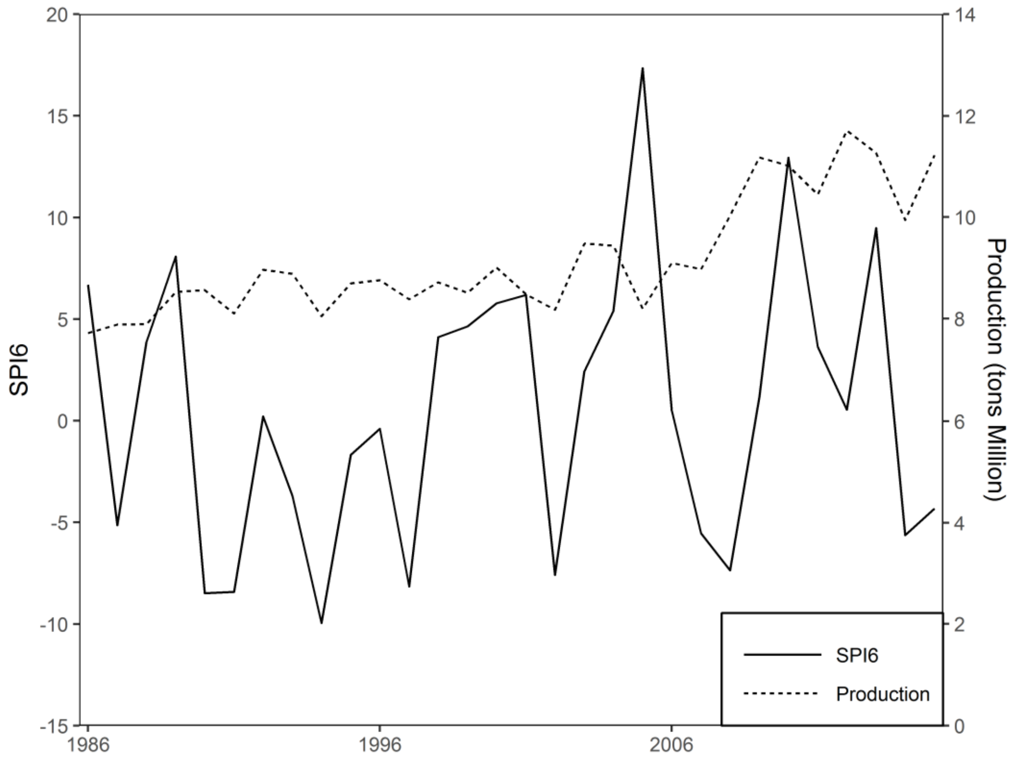


Figure 5-5: Drought index SPI6 and annual rice production for Central Java Province, 1986-2015. Data source: CRU rainfall and Ministry of Agriculture for annual rice production.

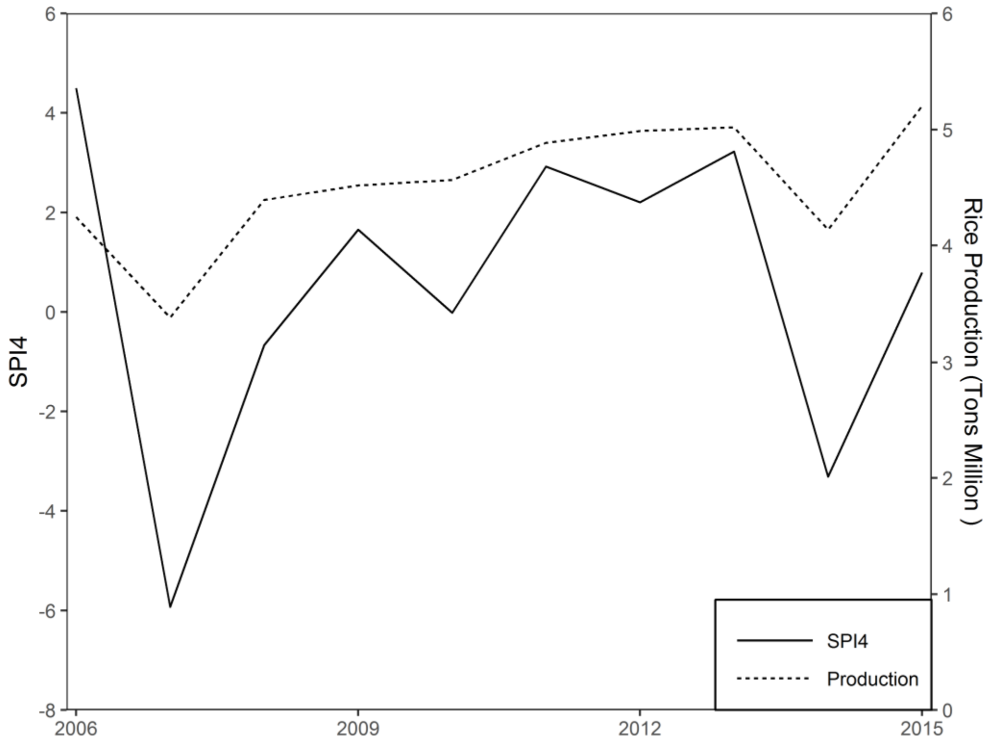


Figure 5-6: Drought index SPI4 and wet season rice production, Central Java Province, 2006-2015. Data source: CRU rainfall and Ministry of Agriculture for annual rice production.

At the district level, consistent patterns are observed with correlation coefficients between annual rice production and SPI12 ranging from 0 to 0.2, and for SPI4 and wet season rice between 0.36 to 0.78. These results suggest focussing the development of a parametric insurance solution on SPI4 and wet season rice.

CHAPTER 6. Development of a Risk Transfer Solution and Validation

Based on the drought indices and the decision to use the time span of the drought indices that best explains volatility in rice production, a parametric insurance product can be developed. A parametric insurance contract that is based on weather indices (such as SPI for example) is fully defined through the sum insured, the trigger (also called strike), the limit and the modality of the pay-out function.

Key Terms of Parametric Insurance Products

The sum insured is typically determined from the underlying assets exposed to adverse weather conditions such as a drought and can be agriculture production, government disaster budget of ad-hoc reliefs or emergency import provisions.

Triggers, limits, and the modality of the pay-out function are integral parts of the *Indemnity Function*, where the parametric insurance contract protects against insufficient and/or excessive realisations of the underlying weather variable (e.g., rainfall deficit quantified through SPI).

The Indemnity I received through the indemnity function for insufficient realisations (deficit) of the underlying index that is based on a weather parameter is defined as[68]

$$I = f(i|x, Tr, Ex) = x \times f(x) = \begin{cases} 0, & if\ i > Tr \\ \dfrac{Tr - i}{Tr - Ex}, & if\ Ex < i \leq Tr \\ 1, & if\ i \leq Tr \end{cases}$$

The indemnity I is a monetary value for a surface unit (e.g., 1 USD/hectare or 10 million USD per province), the variable i is the realised value of the underlying weather parameter, x is the sum insured, Tr is the *Trigger* and Ex is the *Exit* below which level pay-outs seize. The Limit L is defined as $L = Tr - Ex$. The payout function, i.e., how fast the maximum indemnity is reached after the indemnity has been triggered, is mostly defined as *linear* but can be *binary* in that any realised value below the Trigger pays out the full indemnity or *step-wise* in that pay-outs increase with increasing realisations of the index. Exits are used with the aim to reduce exposure and obtain affordable premium rates.

Triggers are often chosen based on i) previous catastrophic events that are relevant from the observed weather parameter (e.g., SPI), ii) realisations of a weather parameter at a certain quantile (e.g., 75%) from historical observations or modelled through probability density functions of the weather variable or iii) a given standard deviation (e.g., 50%) above/below the mean weather variable from historical observations. Based on the Sum Insured and the index nomination, a *Tick Size* (also called Notional) is determined, which consists of the monetary pay-out for each realisation of the weather index composed of underlying weather variable(s).

With all relevant parameters set, the *Pure Risk Premium* can be calculated from the underlying weather parameters and the structure and pay-out function of the index. The Pure Risk Premium is calculated in using i) a probability density function (e.g., e.g., Weibull or Gamma) of the historical weather observations called *Expected Loss Calculation (ELC)*, or ii) historical weather observations from which a *Historical Burn Rate (HBR)* is calculated. The HBR method is more commonly used and considered the benchmark approach for index pricing when 10-30 years of weather data are available. HBR has the advantage over ELC of not requiring the development of a probability density function but has the disadvantage that rare occurrences in realisation of the weather parameter (catastrophes) have not been

[68] Definition with modifications from Vedenov, D.V. and Barnett, B.J. 2004: Efficiency of weather derivatives as primary crop insurance instruments. *Journal of Agricultural and Resource Economics*, 29, 387–403.

experienced within the timeframe of the observation. One way to address the potential lack of catastrophic events in the HBR method, is to introduce a *Catastrophe Loading*. The Commercial Premium Rate is obtained in loading the Pure Premium Rate for administrative costs, capital requirements of the insurer and (in some cases) data uncertainties.

Key Terms for a Parametric Insurance Product for Rice in Central Java

Based on the results of correlation analyses between SPIs of different time spans (12months, 4 months) and rice production (seasonal and annual), a parametric insurance product is developed in this study for wet season rice and 4-months cumulative SPIs (January-April). Once longer seasonal rice statistics are available, further indices can be developed for other than wet season rice production and annual rice production.

For this study, the sum insured is defined based on an assumed value of the underlying wet season production. The production of wet season rice of the last available year in the data series (2015) is 5,201,626 tons which compared to an average of 4,533,571 tons for the period 2006-2015. Farmers produce paddy which gets converted into rice through various processes including de-husking. The milling out-turn in Indonesia is very low (below 60%) and explains most of the gap between farm-gate prices (USD 300) and wholesale prices (USD 700). As the exposure of the Central Java Government in cases of severe droughts is through its disaster relief program to rice farmers, the insured value of a ton of rice is set in this study at USD 100, which reflects a third of the average farm gate price. The sum insured is therefore obtained by multiplying the wet season production with the rice value at farm gate and results for this study in USD 520,162,600, which signifies the value at risk.

The trigger, i.e., the level of drought extent (i.e., SPI value) below which the parametric insurance product starts paying out, is to be determined from the past data. For this study, SPI values (aggregated for the province of Central Java) are analysed over the period 1960-2015. With the absence of data on the Central Java Government's actual expenditure in historical droughts, perceived exposure and disaster declaration reports, the assumption was taken that moderate and severe droughts with an SPI value higher than -5 would cause financial constraints. Over the last 56 years (1960-2015), a total of 18 wet rice seasons showed droughts with SPI values higher than -5, i.e., around one drought event in 3 years.

The exit, below which indemnity is not payable under the parametric insurance product reflects the probably maximum drought intensity (i.e., negativity of SPI values). While theoretically it is possible that no rainfall is received in the wet rice season and results into a very low or close to zero production (the maximum probable drought intensity), a more realistic probable maximum drought intensity needs to be estimated to make the parametric insurance product efficient. The most severe drought in Central Java (i.e. the lowest SPI value) occurred in 1994 (SPI of --9.95), followed by 1976 (-9.89) and 1982 (-9.25). In comparison, the well-known severe Indonesia-wide droughts of 1997 and the most recent event of 2014 produced in Central Java SPI values of -8.15 (1997) and -5.63 (2014) respectively. From the historical data, an exit of an SPI value of -10 would be justified, however, the past climate drought intensity might not reflect the future climate. While statistical simulation can be used to generate more intensive droughts than historically experienced over the last 56 years, the use of outputs from physical models such as General Climate Circulation Models (GCMs) is preferable.

Climate projections from General Circulation Models (see CHAPTER 7 and BOX) offer the opportunity to obtain physically simulated rainfall distributions under the future climate and allow to validate parametric insurance products that are based on historical data. A further application of climate projected rainfall intensity and distribution (reflected in SPI values) is to obtain a better understanding of extreme drought events that might have been experienced in the historical time series. For the purpose of this study, climate projections undertaken by the Tropical Marine Science Institute (TMSI) of the National

University of Singapore (NUS[69]) were used to compute SPIs for the time span of 2016-2040 (see CHAPTER 7). It appears that a drought with an SPI value of -13.32 (Figure 6-1) can be expected in the next 25 years (2016-2040). From this point of view, setting the Exit at -20 seems more realistic in order for the parametric insurance product to provide adequate protection to the Government of Central Java. As a function of the Trigger (SPI value -5) and the Exit (SPI value -20), indemnity would occur under the parametric insurance product for a total of 15 SPI values.

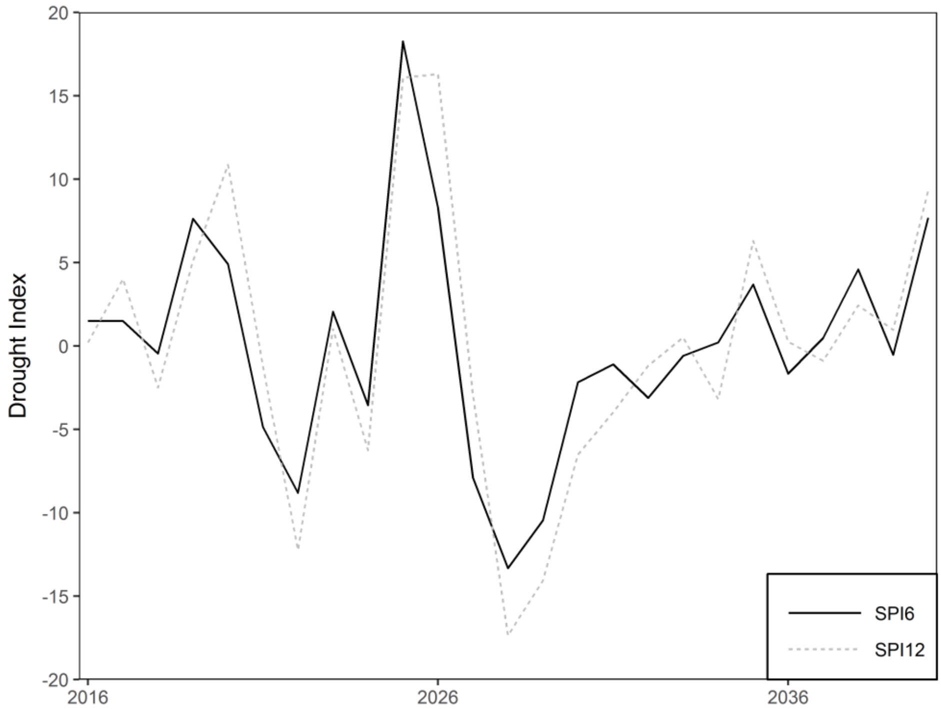


Figure 6-1: Projected Annual SPI-6 and SPI-12 for Central Java Province, 2016-2040. Source: TMSI/NUS.

Once the Trigger and Exit have been defined in function of drought intensity (SPI values), a probable maximum production shortfall must be determined in order to define the Tick Size. In the short time span of 2006-2015 for which season rice production was available for this study, the drought of 2007 produced a production shortfall of 857,000 tons compared to the year before and similarly, 880,000 tons in 2014 compared to 2013. While 10 years of wet season rice production is short to reveal a production trend, particularly in the presence of large reductions in production due to two drought years, there seems to be an increasing trend in production over time. This means that past droughts (e.g., like the 1960s as identified from the SPI time series), will have a larger impact on production (i.e., reductions well above 880,000 tons seen in 2014) than what was experienced in the past. Based on this this perspective, namely increase in production over time, a worst-case but realistic production shortfall of 1 million tons of wet season rice is assumed for this study.

The Tick Value is obtained by dividing the probable maximum production shortfall with the probable maximum drought severity. For the present study, a Tick Value of USD 6,666,667 is obtained with the assumption of a production shortfall of 1 million tons and the indemnity of 15 SPI values. The Limit is determined as USD 100 million as a maximum indemnity of 15 SPI values and a Tick Value of USD 6,666,667 for each SPI value.

[69] *http://www.tmsi.nus.edu.sg*

To obtain the Pure Risk Premium, the *Historical Burn Rate (HBR)* methodology is followed where the computed indemnity of the parametric insurance product for each historical year (1960-2015) and expressed as a ratio of the limit for each historical year (i.e., 56 years of USD 100 million limit), which in turn is expressed in function of the Total Sum Insured. The resulting *Pure Risk Premium Rate* comes to 1.23% of the Total Sum Insured.

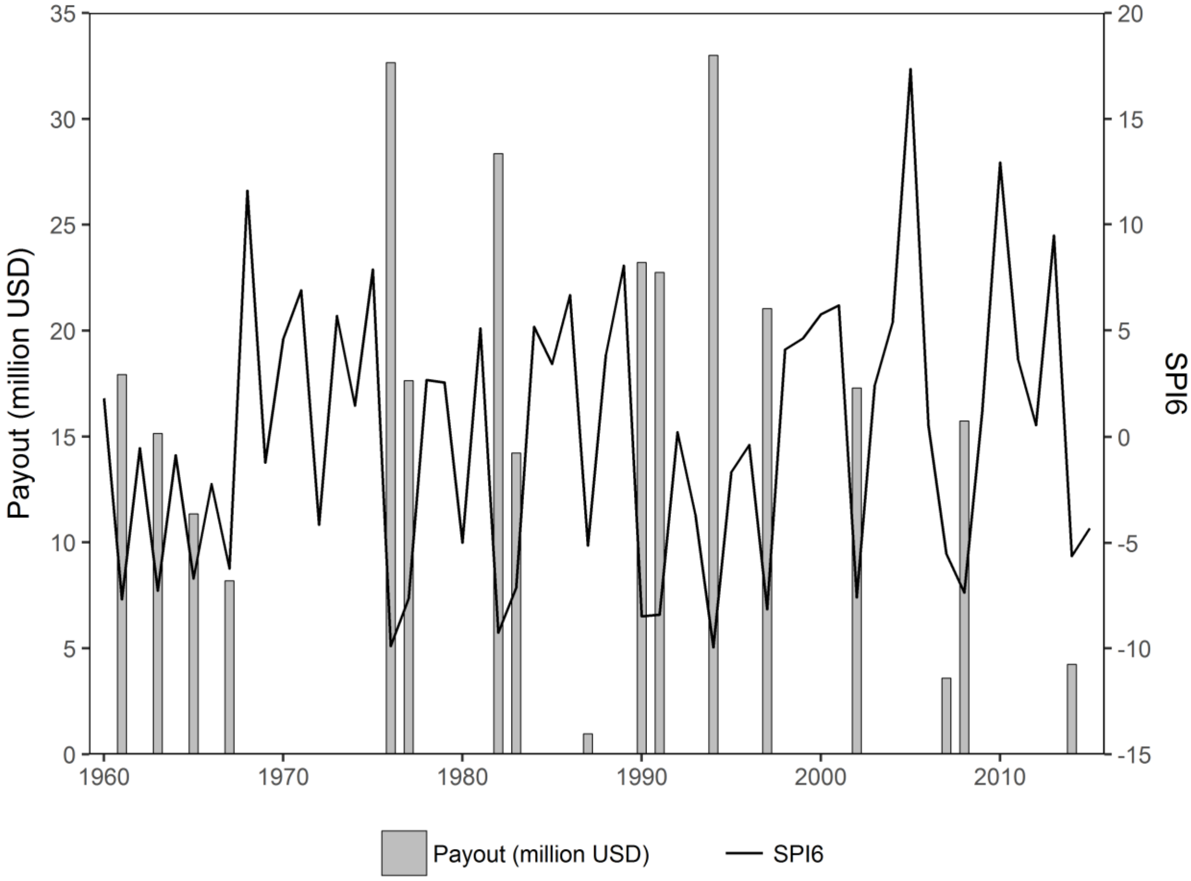


Figure 6-2 Payouts of the parametric insurance product (left axis, columns) and SPI6 (right axis, line) for Central Java Province, 1960-2015. Data source: CRU rainfall.

Over the last 56 years (Figure 6-2), the parametric insurance product pays the highest indemnity in 1994 (USD 33 million), followed by 1976 (USD 32 million), 1982 (28 million), 1990 and 1991 (each USD 22 million). The 1997 drought would pay-out USD 21 million in Central Java and was not as intense as drought in other parts of Indonesia. The parametric insurance products would have paid a total of USD 287 million since 1960.

The insurance terms are summarized as follows:

- Territory: Central Java Province, Indonesia
- Period: 1 January to 30 April (reflecting wet season rice production)
- Sum Insured:
- Index: 4 months SPI value (2 digits) aggregated from 0.5° grid cells over Central Java
- Data Provider Rainfall: to de decided (probably CHIRPS[70])
- Fall-back Data Provider: to be decided

[70] Note that while CRU provides the longest time series of rainfall, updates are only undertaken at irregular intervals. CHRIPS provides high-resolution precipitation data since 1981 with continuous monthly updates. For implementation of this project, CHRIPS data will be investigated and the drought indices be recalculated.

- Trigger: SPI value ≥-5
- Exit: SPI value-≤ 20
- Pay-out Function: linear
- Tick Value: USD 6,666,667 per SPI value
- Limit: USD 100 million
- Pure Risk Premium Rate: 1.23%

CHAPTER 7. Validation of the SPI index with Climate Projections

Climate models, also known General Circulation Models (GCM) are used by the scientific community to assess changes in the global climate based on different climate scenarios and forcing mechanisms. Outputs of GCMs are hardly used in the insurance industry, which risk pricing and modelling essentially relies of past data and *statistical simulations*. The use of *physically generated weather events* (e.g., rainfall patterns from GCMs) and resulting drought indices (e.g., SPI) has the advantages that models are trained on the past climate and reproduce past climate events through mathematical equations of the climate system in a global context. However, the use of a GCM including the downscaling to particular regions requires high computing power and expertise in several disciplines. GCMs are therefore operated at National Weather and Climate Services and leading universities, with the *Intergovernmental Panel on Climate Change (IPCC[71])* overseeing the overall efforts and results.

In this study, and probably as one of the first time in the agriculture risk transfer industries, outputs of GCMs are used to derive drought indices (SPI) under future climate. For this study, the climate-projected SPIs are used to i) estimate a probable maximum drought intensity over Central Java (see CHAPTER 6) and to validate the drought index (SPI) that was developed with past climate data (1960-2015) for the benefit of the parametric insurance product (CHAPTER 7).

BOX: Climate Models

Climate models, also called General Circulation Models (GCM), are based on mathematical representations of the climate-system represented by physical, biological and chemical principles on numerical grids. Complex equations characterize how energy and matter interact in the ocean, atmosphere and land over thousands of three-dimensional grid cells that represent the globe at some 20 different atmospheric layers. Processes are first modelled in each grid cell and passed on to neighbouring cells to compute the exchange of matter and energy over different time dimensions. A climate model includes several coupled sub- models to i) represent the oceans, atmosphere, land and continental ice as well as the fluxes between each other, and ii) model seas ice mechanisms and evapotranspiration over land. The numerical grid of climate models of the highest resolution (100km) is still too large to present small-scale processes such as turbulence in the atmospheric and oceanic boundary layers, impact of topography and thunderstorm development. Therefore, climate models need to be *parameterised* based on empirical evidence and/or theoretical assumptions to account for the large-scale influence of those processes that are not explicitly included in the climate models.

Most climate models are developed for climate projections where changes in climates are simulated in response to emissions of greenhouse gases and aerosols. Climate models then perform experiments out of which scenarios are constructed of how the climate will evolve. Initially, standard (climate change) scenarios were developed based on complex relationships between socioeconomic forces driving greenhouse gas and aerosol emissions and levels to which emissions would increase during the 21st century. Climate prediction uncertainties depend on uncertainties in chemical, physical and social models.

The size of the grid cells (ranging from 100 km to 500 km), the number of time steps (ranging from hours to days) and available computing power used to operate the climate model essentially determine the resolution of the model output. Typical time frames of climate model outputs include daily or monthly parameters such as temperature (minimum, maximum, average), rainfall and a large suite of other climate

[71] *https://www.ipcc.ch*

variables. The models are usually validated using available observations or using gridded products, mostly for temperature and for rainfall.

Though Global Climate Models (GCMs) provide global climate information on key climate variables including precipitation, the mismatch in the spatial resolutions between GCMs and the downstream end-user needs (regional/local) necessitates *downscaling*. Two most common methods of downscaling are the dynamical and statistical. Dynamical downscaling uses a limited area model to simulate physical processes at the sub-regional level while statistical downscaling, involves statistically determined relationships between the observed local response and the observed large-scale climate state are used to calculate projected future local responses to the projected large-scale climate states.

As the understanding of interactions between ocean, atmosphere and land increases and more computing power becomes available, climate models are getting more sophisticated at increased spatial and temporal resolutions. Downscaled climate data is increasingly used as an input to models that then simulate specific impacts of climate variability and change such as e.g., water runoff or crop yields.

For this study, rainfall data from regional climate model simulations of the *Weather Research and Forecasting (WRF[72])* are used. Developed at the National Center for Atmospheric Research (NCAR), USA, the WRF model is suitable for a broad spectrum of applications across scales ranging from meters to thousands of kilometers. The model incorporates advanced numeric and data-assimilation techniques, multiple nesting capabilities and numerous state-of-the-art physics options. WRF is a widely used regional climate model by the climate research community around the globe[73]. The WRF regional climate model has been used by TMSI/NUS for climate studies and projections commissioned by the Government of Singapore for Singapore and SE Asia since 2007[74].

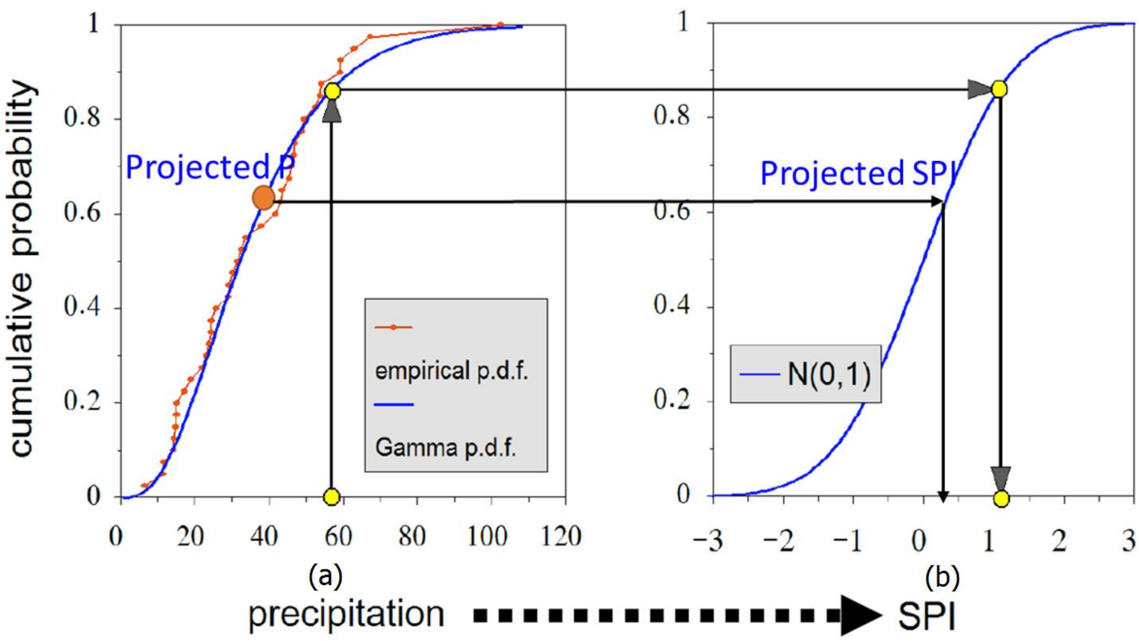
For this study, the climate simulations were performed at a 20-km spatial resolution of the WRF model being driven by global reanalyses ERA-Interim (for initial model performance assessments) and by 3 global climate models: MPI ESM-MR (ECHAM6), CSIRO-ACCESS1.3 and MRI-MIROC5. The baseline historical climates were studied over the period 1986-2005 and the future climate was based on the Representative Concentration Pathways (RCP) scenario 8.5[75], for the period 2016-2040. These RCP scenarios are the new set of emission/projection scenarios under the International Panel on Climate Change (IPCC) recommended for use in the global model simulations of the Coupled Model Intercomparison Project (CMIP) Phase 5, that have been reported in the Fifth Assessment Report (AR5). These scenarios have been developed on the basis of possible net radiative forcing by the end of the century under the influence of anthropogenic climate change[76].

The WRF model simulated precipitation at 6 hourly intervals (accumulated to monthly scales) was used to derive the SPI in the same way as it has been done for the past climate (1960-2015) for all 50 km grids over Central Java, as described in CHAPTER 6. The SPI indices (SPI6) from the climate projections were then compared against observed data (CRU) and for future assessments. For simplicity, the WRF simulations driven by the reanalyses are referred to as ERA-Interim (WRF/ERAI), GCMs MPI-ECHAM6, ACCESS1.3 and MIROC5 as WRF/ERAI, WRF/ECHAM6, WRF/ACCESS and

72 *https://www.mmm.ucar.edu/weather-research-and-forecasting-model*
73 *http://www.wrf-model.org*
74 Raghavan, V.S., Vu, M. T. and Liong, S.Y., 2016: Regional Climate Simulations over Vietnam using the WRF model. *Theoretical and Applied Climatology*, 126, 161-182.
75 *https://www.ipcc.ch/pdf/assessment-report/ar5/syr/AR5_SYR_FINAL_SPM.pdf*
76 *http://sedac.ipcc-data.org/ddc/ar5_scenario_process/RCPs.html*

WRF/MIROC, respectively. For climate projections of drought study, the SPI is computed with referenced to the baseline climate 1986-2005.

The monthly precipitation of baseline climate ('x' months accumulated) was fitted with a gamma distribution (see Cumulative Density Function in Figure 7-1 left) then transformed to normal distribution with mean of 0, variance of 1 (Figure 7-1 right) to find the corresponding SPI values. The fitted model was carried out for baseline climate in order to estimate the baseline SPI. For climate projection, the accumulated projected monthly precipitation is applied to the same Cumulative Density Function and is then applied to an inversed transformation in order to obtain the projected SPI values in normal distribution.



Figure

Figure 7-1: Computation of future SPIs with reference to the baseline SPI. Source: TMSI/NUS.

The current climate projections and SPIs from the projected rainfall intensity and distribution are available for 2016-2040. For a further project that goes beyond the scope of this study, climate-projected SPIs can be developed for the period 2041-2100, which will add additional robustness to the analyses already performed under this study.

Climate-Projected SPIs over Central Java

The comparison of historical droughts (negative SPI values, based on CRU data from 1986-2005) and outputs of the GCM (WRF/ERAI) for the past climate (negative SPI values, 1986-2005), shows that the GCM is able to capture certain severe droughts during strong El Nino events during 1987, 1994-1995, 1997 (Figure 7-2). However, there are some discrepancy over these two data sets as seen in the early 1990s where WRF/ERAI showing wet patterns as compared to CRU (drought). In 1991, there was a strong El Nino event, and CRU is able to signify the El Nino with drought condition, whilst WRF/ERAI only shows very minor decreasing in its SPI value. This might be due to the underestimation of precipitation data set from WRF/ERAI compared to CRU for the 1990s, leading to discrepancy in detecting the drought event.

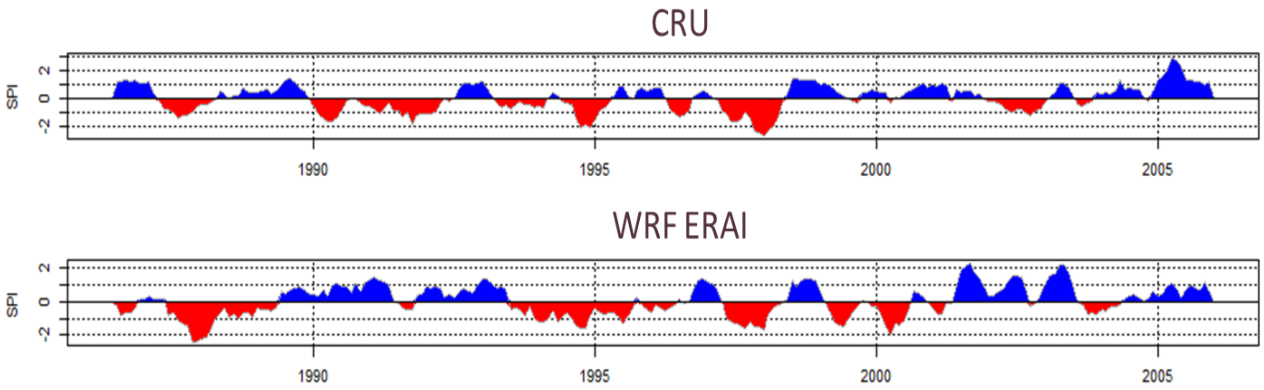


Figure 7-2: SPI index (SPI6) for baseline climate using CRU and WRF/ERAI data over Central Java. Source: TMSI/NUS

The drought characteristics using past climate data (CRU) and from GCMS (including WRF/ERAI) shows for Central Java that WRF/ERAI is comparable to CRU for SPI value for the baseline climate that (Table 7-1). Further, CRU and WRF/ERAI agree well with the same number of drought and similar values for drought deficit and frequency. However, WRF/ERAI underestimate the number of droughts. The drought deficit is simulated well by WRF/ACCESS and the model ensemble is also able to capture this. In terms of drought frequency, the model ensemble shows the best match, followed by WRF/MIROC and WRF/ACCESS.

Table 7-1: Drought Characteristics for observation of CRU (past climate, 1986-2005) and WRF GCMs for SPIs over Central Java

Base Climate ***(1986-2005)***	**Global Circulation Models (GCM)**					
SPI	**CRU**	**WRF/ERAI**	**WRF/ECHAM6**	**WRF/ACCESS**	**WRF/MIROC**	**ENSEMBLE**
Number of Droughts	7	7	6	5	4	6
Duration	13 9 21 11 5 15 14	17 14 13 14 7 7 8	12 22 8 13 8 37	17 11 17 21 17	11 45 10 18	10 35 13 13 5 14
Deficit	-86.43	-78.37	-77.01	-80.69	-72.56	-80.6
Frequency	0.39	0.36	0.44	0.36	0.37	0.39

The projected SPI values (SPI6) for Central Java for the time 2016-2040, indicate the drought characteristics for the projected period with reference to the baseline climate (1986-2005). Results reveal that, WRF/ECHAM6 is the “driest” model with the highest number of droughts, deficits and frequency (Table 7-2). On the other hand, the WRF/ACCESS is the “wettest” model with the least drought characteristics.

Table 7-2: Drought characteristics for projected climate 2016-2040, RCP8.5 for Central Java using 4 versions of the WRF GCM.

Climate (2016-2040)	***Global Circulation Models (GCM)***

SPI	WRF/ECHAM6	WRF/ACCESS	WRF/MIROC	ENSEMBLE
Number of Droughts	7	4	5	4
Duration	8 3 22 7 36 12 10	7 6 6 5	15 10 10 10 11	14 11 11 7
Deficit	-85.89	-20.08	-49.49	-40.35
Frequency	0.33	0.08	0.19	0.14

Validation of the Parametric Insurance Product for Rice in Central Java

The climate projected drought intensity (negative SPI values) and temporal distribution (2016-2040) reveals that i) climate-projected negative SPIs show a larger variability (next 25 years) compared to last 56 years, ii) the highest climate-projected SPI is -13.3 (2028[77]) compared to -9.95 (1994), iii) climate-projected SPIs show the likelihood of a four year period (2027-2030) of consecutive drought occurrence at different intensities (SPI values of -7.9, -13.3, -10.5 and -2.17) which has occurred in the past (1961-1964) but at lower intensities (SPI values -7.7, -0.6, -7.3 and -0.9) and iv) climate-projected positive SPIs (excessive rainfall/flood) are comparable to the last 56 years (Figure 7-3). From the climate projections, it results that drought intensity is likely to increase in Central Java, while the intensity of flash floods/excessive rainfall is likely to remain at current levels.

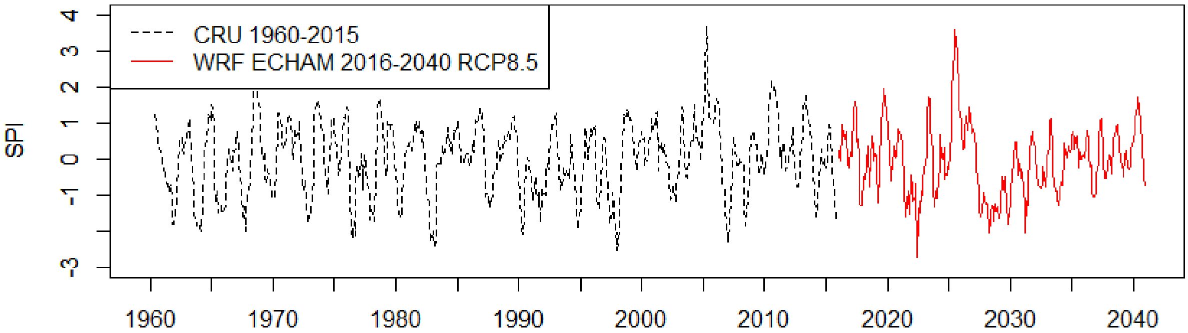


Figure 7-3: SPI6 based on the past climate (1960-2015) and the future climate (2016-2040). Data source: CRU for baseline rainfall and WRF/ECHAM RCP8.5 for projection rainfall by TMSI/NUS.

Climate projected SPIs reveal the unique opportunity to add an additional 25 years of possible drought events (2016-2040) to validate the SPI index of the parametric insurance product. As drought intensity (negative SPI values) increases under the climate projections, the highest payout reaches now USD 55.5 million (2028), which is equivalent to about half of the maximum payout (USD 100 million). Further, the Pure Risk Premium Rate increases from 1.23% (CHAPTER 6) to 1.26% with the climate projected SPIs. Over the last 81 years, which includes 56 years of historical data and 25 years of climate projected data (Figure 7-4), the total payout of the parametric insurance product reaches USD 424 million compared to USD 287 million (historical years of 1960-2015 only).

[77] Note that while a severe drought is projected to occur in the future, this does not mean that it will happen in the year 2028.

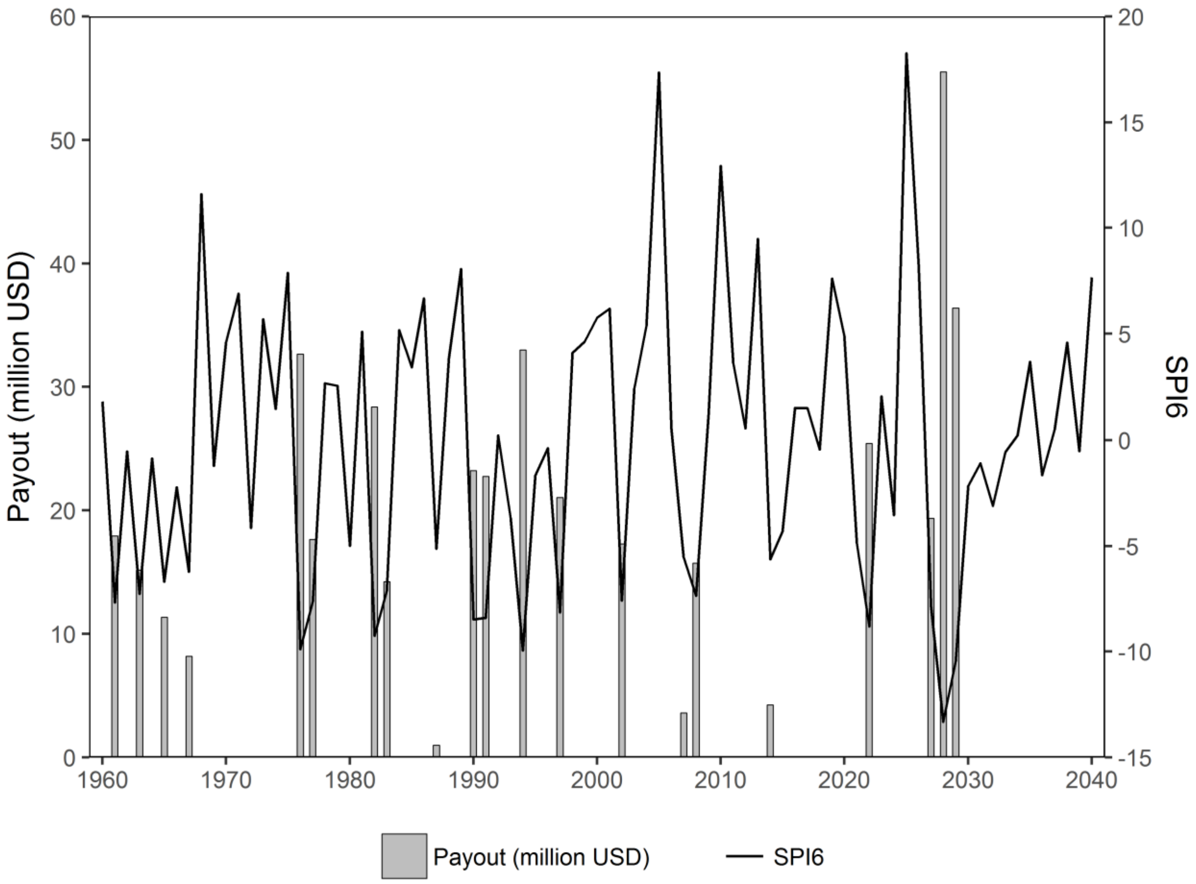


Figure 7-4: Payouts of the parametric insurance product (left axis, columns) and SPI6 (right axis, line) with the limit shown in yellow (i.e., SPI values between -5 and -20) for i) 1960-2015 based on CRU rainfall data and ii) 2016-2040 based on climate projections with the WRF/ERAI GCM. Data source: CRU for baseline rainfall and WRF/ECHAM RCP8.5 for projection rainfall by TMSI/NUS

CHAPTER 8 Regulatory/Policy Framework in Indonesia

One of the main beneficiaries of a parametric insurance solutions for drought impact on rice production in Central Java is the Central Java Government, which has obligations towards farmers such as ad-hoc disaster payments. As drought disasters are of systemic nature, it is highly likely that the entire province of Central Java can be impacted by the same drought and most (if not all) farmers suffer shortfalls in wet season rice production. This can cause unexpected budget needs for the Central Java Government. As pervious cases where governments bought parametric insurance has demonstrated, the necessary regulatory and policy framework needs to be in implemented.

For Indonesia, it seems possible for a provincial government to enter an insurance agreement and purchase an insurance contract to protect state assets and implement program and activities under the regulations as follows:

- Government Regulation No 45/2013 (article 111) allows for the Minister of Finance to enter a risk management contract with an insurance service provider and/or risk management agent
- Government Regulation No. 27/2014 (article 45) states that the asset manager (i.e., the line ministry) can purchase insurance policies to protect state assets
- The Ministry of Home Affairs Regional Financial Management Guidelines No. 13/2006 (article 52) allows for local governments (LGs) to pay insurance premiums, as insurance is classified as a permissible expenditure for the use of goods and services in implementing their program and activities.

In terms of ability and sustainability to pay for insurance, budget cannot be guaranteed beyond one fiscal year due to Parliament restrictions as the appropriate budget is only approved once in a fiscal year. To deal with this annual expenditure and appropriation constraint, the Ministry of Finance has permitted line ministries to enter multi-year contracts (MYC) for some priority programs that can be implemented in medium-term. In case agriculture and/or weather index insurance is classified as priority, it can fall under the MYC.

Following detailed assessment of various regulations related to the LGs disaster management financing and insurance, the World Bank made the following recommendations:

- Requiring LGs to regularly budget for and acquire adequate insurance coverage for their own assets and fiscal liabilities that may be triggered by natural disasters
- Introducing a rigorous and verifiable process for determining economic losses caused by natural disasters at the local level (e.g. independent professional loss assessment service providers should be considered)
- Introducing clearly defined rules (based on international best practices) for insurance purchasing by LGs and government agencies
- Allowing LGs to use potential insurance indemnity payouts toward co-financing central government disaster reconstruction grants

The National Agency for Disaster Management (BNPB), during a high-level bilateral meeting with World Bank officials in 2015, had informed that the above mentioned structural problems in the system could be rectified through an amendment of the Disaster Management Law (Law 24/2007) currently under review..

CHAPTER 9 Conclusion and Outlook

This study has revealed that droughts, which are quantified through a drought index (Standard Precipitation Index) can reliably be used as the basis for a parametric insurance product for rice production shortfalls with a payout at the resolution of an Indonesian province.

The parametric insurance product can be improved if the following data becomes additionally available: i) Indonesian weather station data in Central Java province to validate the CRU gridded climate data used to develop the drought indices (1961-2015), ii) wet season rice production and yield for a longer period than what was available for this study (2006-2015), iii) confirmation of rice prices in terms of exposure to the Government of Central Java under severe drought conditions, iv) ad-hoc disaster budgets and actual payouts of the Government of Central Java to support rice farmers in case of severe droughts, v) other loss proxies such as area impacted by drought and other natural disasters and v) higher resolution and more updated irrigation mask that show irrigation levels per rice season on a regular grid.

While it seems that the Government of Central Java can buy catastrophe risk protection for agriculture assets per regulation, this needs to be confirmed with the Ministry of Home Affairs and also Ministry of Finance, GoI. As ex-ante risk transfer is still new to Indonesia, the concept itself as well as the benefits compared to post-disaster risk funding needs to be more emphasized in discussions and through workshops. In a next step and following continued interest in Indonesia the following will be undertaken i) finalising the parametric insurance structure based on the availability of additional data and discussion with the key stakeholders and ii) cost-benefit analysis of risk transfer relative to risk funding (contingent credit and loans) in case of drought disasters on rice production in Central Java.

Given the flexibility of parametric insurance products in general and the methodology develop for this study, the payout function of the parametric insurance product can be adjusted using parameters such as i) sliding-scale payout in function of drought intensity (negative SPI values) with higher payouts for highly negative SPIs (most severe droughts) than for moderate droughts and ii) introduction of multiyear features (e.g., a three year period of insurance) with a profit commission in years without payout. Based on the concept developed in this study, drought indices can be developed for other Indonesian province and validated in case the relevant data are available. The parametric insurance product can be structured in a way that payout occurs over several or all provinces. Similarly, the product could be structured to payout at the resolution of a district.

Ex-ante risk transfer is a proven concept to protect government budgets in case of large-scale disasters and is increasingly used by governments to transfer risks from agriculture assets (mainly crop, livestock and forestry exposure).

APPENDIX 1 Standard Precipitation Index (SPI)

The *Standard Precipitation Index (SPI)* was first introduced by McKee et al. in 1993[78]. Briefly, he SPI is calculated using the following steps[79]: i) identify a probability density function that best fit the long-term time series of rainfall observations, ii) construct a set of moving windows of the rainfall observation series depending on the time scale of interest. Here, one constructed moving windows of total precipitation corresponding to 3, 6 and 12 months to derive SPI 3, SPI 6 and SPI 12 respectively, iii) apply the selected probability density function to the time series (from step 2) to construct the cumulative probability distribution and iv) apply the inverse normal (Gaussian) function (with mean zero and variance one) to the cumulative probability distribution function to construct the SPI time series. Based on the Kolmogorov-Smirnov (K-S) and chi-square test statistics, it was found that the monthly rainfall series followed a gamma distribution[80].

The first step in calculating the SPI index involves fitting of a Gamma distribution function to the rainfall observations x:

$$g(x) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta}$$

whereas $\alpha > 0$ is a shape parameter, $\beta > 0$ is a scale parameter and $\Gamma(\alpha)$ is the gamma distribution function. The parameters of the gamma probability density function can be estimated from the rainfall data using maximum likelihood methods for each location and time span.

$$\tilde{\alpha} = \frac{1}{4A}\left(1 + \sqrt{1 + \frac{4A}{3}}\right) \; and \; \tilde{\beta} = \frac{\bar{x}}{\tilde{\alpha}}$$

Whereas $A = \ln(\bar{x}) - \frac{\sum \ln(x)}{n}$ and where n is the number of rainfall observations where rainfall occurred. The parameters $\tilde{\alpha}$ and $\tilde{\beta}$ are then used in the cumulative probability function for a given time scale (e.g., a month). The cumulative probability with a time span of $t = x/\tilde{\beta}$ for the gamma distribution function becomes:

$$G(x) = \frac{1}{\Gamma(\widetilde{\alpha})} \int_0^x t^{\tilde{\alpha}-1}\, e^{-t} dt$$

As the gamma function $G(x)$ is undefined for $x = 0$ and rainfall may well be zero, the cumulative probability density function becomes:

$$H(x) = q + (1-q)G(x)$$

Whereas q is the probability of zero rainfall.

In a second step, $H(x)$ is transformed into a normal variable Z by means of the following approximation with Z or the SPI having a positive if $0.5 < H(x) \leq 1$ and a negative value for $0 < H(x) \leq 0.5$ with the negative value shown here as:

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[78] McKee, T.B., Doesken, N.J. and Kleist, J., 1993: The relationship of drought frequency and duration to time scales. In: *Proc. 8th Conf. on Appl. Clim. Am. Meteorol. Soc.* Boston, Massachusetts, 179–184.

[79] Guttman, N.B., 1999: Accepting the Standardized Precipitation Index: a calculation algorithm. *J. Amer. Water. Res. Ass.*, 35(2), 311-322.

[80] The concept of SPI computation is comprehensively summarised in Mishra, A.K. and Desai, V.R., 2005: Drought forecasting using stochastic models. *J. Stochastic Environ. Res. Risk. Assess.*, 19, 326–339.

$$Z = SPI = -\left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right)$$

Whereas $t = \sqrt{\ln(\frac{1}{(H(x))^2})}$ for $0.5 < H(x) \leq 1$ and with the following parameters:

$c_0 = 2.515517$ $d_1 = 1.432788$

$c_1 = 0.802853$ $d_2 = 0.189269$

$c_3 = 0.010328$ $d_3 = 0.001308$

The World Meteorology Organisation (WMO) provides a comprehensive guide on SPI[81] and several National Weather Services provide SPI maps online and software to compute SPIs[82].

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[81] World Meteorology Organisation (WMO), 2012: Standardized Precipitation Index - User Guide. WMO-No. 1090, Geneva, Switzerland, 24p.

[82] E.g., see http://drought.unl.edu/MonitoringTools/DownloadableSPIProgram.aspx (accessed in May 2017)

APPENDIX 2 Standard Precipitation Evapotranspiration Index (SPEI)

The Standardised Precipitation Evapotranspiration Index (SPEI) is a relatively new drought index that uses the rainfall that forms the basis of SPI but additionally uses temperature to determine the difference between precipitation and potential evapotranspiration (PET) to represent a basic climatic water balance. Like SPI, SPEI has an intensity scale with both positive and negative values that identify wet and dry events and can be computed for various time periods. The calculation of PET is in itself complex in that several parameters such as surface temperature air humidity, soil incoming radiation, water vapour pressure and heat fluxes are necessary. The most common method to directly derive PET from weather station data involves simple methods that require only temperature data (e.g., *Thornthwaite equation*) to complex methods that require values for solar radiation, temperature, wind speed and relative humidity (e.g., the *Penman–Monteith* method). Using the Thornthwaite equation, SPEI is calculated through the following key steps[83]:

$$PET = 16K\left(\frac{10T}{I}\right)^{m}$$

With T as the monthly mean temperature in °C, I as the heat index calculated as the sum of 12 monthly index values i calculated through $i = (T/5)^{1.514}$ and $m$as a coefficient that depends on I computed as $m = 6.75 \times 10^{-7} I^3 - 7.71 \times 10^{-5}\, I^2 + 1.79 \times 10^{-2} I + 0.492$. Kas a correction coefficient calculated as a function of the latitude and month as $K = (N/12) \times (NDM/30)$ and NDMas the number of days of the month and N representing the maximum number of sunshine hours which can be calculated in function of the hourly angle of sun rising as a function of latitude.

The difference between PET and precipitation P for a month i, which presents a simple measure of the water surplus or excess, is calculated as

$$D_i = P_i - PET_i$$

The standardisation of SPI is based on a two-parameter Gamma distribution, a log-logistic distribution function is used for SPEI defined as

$$F(x) = \left[1 + \left(\frac{\alpha}{x - \gamma}\right)^{\beta}\right]^{-1}$$

With α, β and γ representing scale, shape and origin parameters which can be obtained through the L-moments procedure[84].

Table A2-1. SPEI value classification	
SPEI Value	**Classification**
> -0.5	No drought
-1.0 to -0.5	Light drought
-1.5 to -1.0	Moderate drought
-2.0 to -1.0	Severe drought
<-2.0	Extreme drought

[83] Vicente-Serrano, S.M., Begueria, S. and Lopez-Moreno, J.I., 2010: A multiscalar drought index sensitive to global warming: The standardized precipitation evapotranspiration index. *J. Clim.* 23 (7), 1696–1718.
[84] Ahmad, M.I, Sinclair, C.D. and Werritty, A., 1988: Log-logistic flood frequency analysis. *J. Hydrol.*, 98, 205–224.