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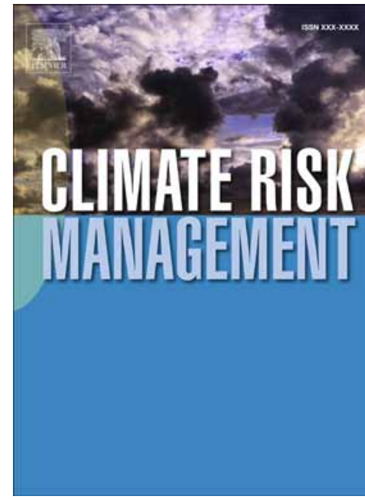

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Historical and future seasonal rainfall variability in Nusa Tenggara Barat Province, Indonesia: implications for the agriculture and water sectors

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Abstract

Climate change impacts are most likely to be felt by resource-dependent communities, and consequently locally-relevant data is necessary to inform livelihood adaptation planning. This paper presents information for historical and future seasonal rainfall variability in Nusa Tenggara Barat (NTB) Province, Indonesia, where rural livelihoods are highly vulnerable to current climate variability and future change. Historical rainfall variability is investigated using observational data from two stations located on the islands of Lombok and Sumbawa. Future rainfall is examined using an ensemble of six downscaled climate model simulations at a spatial resolution of 14 km for 1971-2100, applying the IPCC SRES-A2 'Business as Usual' emissions scenario, and the six original Global Climate Models (GCMs). Analyses of the observed seasonal rainfall data highlight cyclical variability and long-term declines. The observed periodicities are of about 2-4, 5, 8, 11, and 40-50 years. Furthermore, dry season rainfall is significantly correlated with the El Niño Southern Oscillation (ENSO), while wet season rainfall is weakly correlated with ENSO. The simulated rainfall data reproduces the observed seasonal cycle very well, but overestimates the magnitude of rainfall and underestimates inter-annual rainfall variability. The models also show that the observed rainfall periodicities will continue throughout the 21st century. The models project that rainfall will decline, although with wide ranges of uncertainty, depending on season and location. Crop water demand estimates show that the projected changes will potentially impact the first growing period for rice during November-March. Rainfall may also be insufficient to meet water demand for many crops in the second growing period of March-June, when high value commodities such as chillies and tobacco are produced. The results reinforce the importance to consider all uncertainties when utilizing climate projections in subsequent impact assessments. Recommendations on the effective presentation of these results to inform multi-stakeholder adaptation planning for livelihoods, agriculture and irrigation are given.

1. Introduction

Climate change impacts are most likely to be felt at the local scale by resource-dependent communities (Füssel, 2007). Hence generating and effectively communicating locally-relevant climate change information is an important pre-requisite for informed decision-making and livelihood adaptation planning (Srinivasan et al. 2011; Kirono et al. 2014). At the minimum, information should include climate variability and change which has been experienced historically and may be expected in the future, plus the uncertainties that exist around these estimates. For example, knowledge of rainfall variability on a year-to-year time scale provides useful guidance for the management of the agricultural and water resource sectors, while that on a decade-to-century time scale enables better-informed strategic decision-making for investments in infrastructure such as irrigation and water storage (Srinivasan et al. 2011).

One of the primary challenges is that information about projected climate is usually only available at global and national scales, and is rarely available at the sub-national and local scale, especially in less developed countries (Birkmann and Teichman, 2010). This is also true in Indonesia where little scientific data on current climate change exists (Suroso et al. 2009). Hence there is a gap in research and capacity to monitor and project climate change, particularly at sub-national and local scales (DNPI 2011; 2010) where adaptation planning and action needs to occur (Butler et al. this issue a).

According to the Indonesian National Council on Climate Change (DNPI, 2010), the limited scientific basis for quantifying climate change in Indonesia can be attributed to at least two reasons. Firstly, there is a lack of well-documented, spatially-distributed and long-term observational data for key climate variables. Secondly, existing studies mostly rely on global climate models (GCMs), and do not provide finer spatial resolution required to better understand local scale vulnerabilities in order to formulate and prioritise adaptation actions. The Indonesia Climate Change Sectoral Roadmap (ICCSR) (MoE, 2009) and DNPI (2010) have called for studies which can provide the empirical basis for climate change impacts, and that they should combine observations, data analysis, modelling and projections. These studies are required to achieve one of the primary goals of the ICCSR, namely "risks from climate change impacts on all sectors of development will be considerably reduced in year 2030, through public awareness, strengthened capacity, improved knowledge management, and the application of adaptive technology" (MoE, 2009 p. 10).

This study provides empirical information on historical and future seasonal rainfall variability based on observation and modelling. It focuses on the islands of Lombok and Sumbawa in the province of Nusa Tenggara Barat (NTB), which is one of the poorest regions of Indonesia, and where communities are highly dependent on agriculture and irrigation water infrastructure for their livelihoods (Butler et al. 2014). Specifically, this study aims to: 1) document the historical seasonal rainfall variability and trends in NTB from rainfall station data; 2) describe the likely future seasonal rainfall variability and trends using downscaled climate simulation data (McGregor et al. this issue) and the source GCM data, and 3) assess the potential implications for the agriculture and water sectors in NTB. This information was applied in participatory adaptation planning involving multiple stakeholders (Butler et al. this issue b, Butler et al. 2015), and for modelling the potential impacts on ecosystem services and livelihoods (Skewes et al. this issue). This required the presentation of data and results in a form that was accessible to stakeholders ranging from communities, government officials and other scientists (Butler et al. this issue b).

2. Data

2.1. Observed data

This study uses rainfall station data because gridded observed data are not available for NTB, and the available global gridded rainfall data sets (such as the Climate Research Unit (CRU) (Hulme, 1992) with a 2.5^o x 3.75^o resolution; and the Aphrodite's Water Resources or (APHRO_MA) (Yatagai et al. 2012) with a 0.5^o resolution) are too coarse for use in small island geographies such as NTB. To select the stations, we considered that, as suggested by Alexandersson (1986), the study of historical climate variability and change should utilise reliable data that are free of artificial trends or changes. Artefacts of measurement caused by changes in observation practice, equipment, site exposure, and location can lead to misleading results when used in trend analyses (Karl et al. 1993).

There are currently more than 30 rainfall stations distributed across NTB, with varying lengths of record and degree of completeness. Among these are two stations which have more than 40 years of monthly rainfall records, and have been scrutinized for data quality, consistency, and missing values (Kirono, 2002). These are Ampenan (in west Lombok) and Sumbawa (in west Sumbawa; Figure 1), and they are among the 526 Indonesian stations in the World Meteorological Organization-National Oceanic and Atmospheric Administration (WMO-NOAA) project on the Global Historical Climatology Network database (Vose et al. 1992). Thus, they are included in the development of many global data sets including the CRU and the APHRO_MA mentioned above.

At the time of the study, Ampenan had monthly rainfall data for 1950-2010, while Sumbawa had data for 1961-2010. The monthly data were aggregated into seasonal data using the definition of the Indonesian Agency for Meteorology, Climatology and Geophysics (BMKG) (2013), whereby in NTB the normal dry season period is April-October, and the wet season is November-March.

2.2. Simulated data

Simulated rainfall data are commonly developed through the use of outputs of coupled atmosphere-ocean general circulation models (AOGCMs or simply GCMs), since at present they represent the most credible tools for estimating the future response of global climate to anthropogenic greenhouse gas emissions. However, outputs from GCM simulations are spatially too coarse (approximately 200 km) for local climate change adaptation studies, particularly on islands where steep climate gradients exist, requiring a finer scale of resolution (McGregor et al. this issue). Many approaches have been proposed to 'downscale' information from GCM outputs (for a complete review, see Fowler et al. 2007). McGregor et al. (this issue) have simulated climate over the eastern Indonesian region using the CSIRO Conformal Cubic Atmospheric Model (CCAM) at 14 km horizontal resolution for 1971-2100. Their work uses outputs from six GCMs, available in the third Coupled Model Intercomparison Project (CMIP3), forced with the SRES-A2 'Business as Usual' emissions scenario (see McGregor et al., this issue, for details). These outputs were applied in this study.

The simulated downscaled monthly rainfall data for Ampenan and Sumbawa were first extracted from the cells in the gridded simulation data set. Subsequently, the monthly simulated rainfall was aggregated into a seasonal rainfall time series as defined in 2.1. Monthly simulated data was also directly used in the impact analysis for agriculture and water in Section 5.

The same method was applied for extracting monthly time series from the original or host GCMs. These time series were considered in calculating future projections and assessing potential impacts in Section 5. In doing so, this study covers all possible sources of uncertainties, especially those related to climate modeling.

3. Historical observed rainfall variability and trends

3.1. Rainfall climatology

The climate of NTB is strongly influenced by monsoon and trade winds which are responsible for the two distinct seasons experienced across the entire Indonesian archipelago. The Indonesian dry season occurs as a result of the south-easterly trade winds pushing dry Australian continental air masses toward the archipelago, while the wet season occurs when the monsoon winds blow from a north-westerly direction, carrying air masses from mainland Asia and the Indo-west Pacific Ocean.

The wet season onset starts in late August in the north-western part of Sumatera and propagates eastward and southward (Tanaka, 1994; Kirono, 2004). It reaches NTB around November and retreats around March, resulting in an average wet season length of 5 months. Furthermore, as the north-westerly monsoon winds pass over west Indonesia before reaching NTB, the air masses have already lost much of their moisture. Therefore, NTB is drier compared to the more western part of Indonesia (Kirono, 2004).

Additionally, these regional wind patterns interact with local topographic features to cause spatial variation of rainfall throughout Lombok and Sumbawa (McGregor et al. this issue). The western parts of the islands are slightly wetter than the eastern parts since the monsoon starts earlier than in the east and hence Ampenan has a slightly higher mean annual rainfall (1571 mm) compared to Sumbawa (1368 mm). However, the two still share a relatively similar monsoonal cycle which is typical across NTB, peaking around January and receding around July (Aldrian and Susanto, 2003). The mean rainfall for the wet season for Ampenan and Sumbawa is relatively similar (1113 mm and 1110 mm, respectively). For dry season rainfall, Ampenan has a higher value (458 mm) than Sumbawa (259 mm).

3.2. Seasonal rainfall variability

Time series of the wet and dry season rainfall in both stations is presented in Figure 2. Firstly, they show a very high year-to-year or inter-annual variability. The coefficient of variation (defined as the ratio of the standard deviation to the mean) can be larger than one-unit during the dry season (see also Section 4). Secondly, there is multi-year periodicity and inter-decadal variability, evident from the fluctuation of the 5-year moving average. Thirdly, there are long-term declining trends which are statistically significant ($p < 0.1$), except for dry season rainfall in Sumbawa.

To quantify the presence of various periodicities or modes of variability, a multitaper-spectral analysis with a harmonic F-test statistic (e.g. Thomson 1982; Karim, 2014) using the 'Packages multitaper' in R (http://github.com/wesleyburr/multitaper) was conducted. The results (Table 1) indicate three or more periodicities that are significant at the 95% confidence level, except the dry season rainfall in Sumbawa which shows only one significant periodicity (i.e. at around 5 years).

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The significant periodicity in the order of 40 and 50 years possibly implies that the observed negative trends in Figure 2 may be a representation of long-term periodicities. Future analysis using an updated and much longer data set is needed to confirm this. Also, it must be noted that the Sumbawa data length is only 50 years. Hence the finding of a significant wet season periodicity for about 50 years still needs to be reexamined.

Significant periodicities in the order of 2-4, 5, and 8 years may be associated with the periodicity of the ENSO phenomena (Chen, 1982; Rasmusson and Carpenter, 1982), while the eleven year cycle is close to that of sunspots.

To examine the association between rainfall and ENSO, Figure 3 presents the box plots of rainfall anomaly for different ENSO event categories (i.e. La Niña, Neutral and El Niño as defined in http://www.longpaddock.qld.gov.au/). The simultaneous coefficient correlations between the de-trended seasonal rainfall and the de-trended Troup Southern Oscillation Index (SOI), as a measure of the association between rainfall and ENSO, are also provided. They suggest a close association between ENSO and dry season rainfall in both stations. Meanwhile, the association for the wet season is not as clear as that for the dry season.

These findings are consistent with those of previous studies in Indonesia, which show that the rainfall-ENSO relationship varies with season and regions (Kirono, 2000; McBride et al. 2003; Aldrian and Susanto, 2003).

4. Future rainfall variability

4.1. Comparison of observed and simulated rainfall climatology

A more detailed analysis of model validation is presented in McGregor et al. (this issue). Therefore, only the comparison with rainfall is shown here (Figure 4). The simulations closely follow the seasonal cycle of observed rainfall, even though they tend to overestimate the magnitude of rainfall as also found by McGregor et al. (this issue). The simulated data also underestimate the interannual rainfall variability, as their coefficient of variation is always lower than the observed. To reduce this effect, rainfall projections presented in Section 4.2. are shown as the percentage change from the model's baseline.

4.2. Simulated future seasonal rainfall variability and projected change

Figure 5 plots the same information as shown in Figure 2, but for simulated dry season rainfall for Sumbawa for 1971 to 2100. Although not all results are presented here, all models indicate that the observed variability will remain in the future.

To quantify modes of variability during the 21st century (2000-2100), in the downscaled model data the multi-model mean was subjected to the same multitaper-spectral analysis as mentioned in Section 3.2. Overall, the downscaled results (not shown here) indicate similar periodicities to those observed for the 20th century, namely around 2-3, 5-8, 10-15, 20, and 67 years.

Figure 6 illustrates that not all downscaled model data indicate similar long-term trends, leading to some differences in future rainfall projections between the six downscaled simulations. In this case, the median of all six simulations indicates little long-term change in the dry season and a small negative trend in wet season rainfall. Also, the magnitude of the trend is smaller compared to the multi-model range of uncertainty (represented as the maximum and minimum values).

When presented as the percentage change in mean seasonal rainfall by the 2030s and 2050s relative to the 1990s (1971-2000) (shown in red in Figure 7), there is a projected decrease in dry and wet season rainfall, but with a large multi-model spread, consistent with Figure 5 and 6. For example, in Ampenan dry season rainfall is projected to decline by around 2%, with a projected range of +3% to -18% by the 2030s and 0.2% (+8% to -25%) by the 2050s. Wet season rainfall is also projected to decline by around 5% (-2% to -8%), with a strong consensus amongst models in Ampenan.

Figure 7 also plots the projected changes according to the original six GCMs (shown in blue). There are differences in results derived from the two climate simulations. Firstly, GCMs projected changes for both Ampenan and Sumbawa are relatively the same (due to the coarse spatial resolution of GCMs) whereas the downscaled results vary between the two stations. Secondly, the range of uncertainty in GCM projections is mostly wider than that in the downscaled projections. Lastly, the downscaled simulations project a decrease in wet season rainfall compared to no change in the GCMs, and no change in dry season rainfall compared to a decrease in the GCMs, particularly for 2050s.

The regional climate simulations used in this study are downscaled from CMIP3 GCMs used in the IPCC AR4 Report (IPCC, 2007), not from CMIP5 GCMs used in the IPCC AR5 Report (IPCC, 2013). Nonetheless, the projected changes from the host CMIP3 GCMs (shown in blue in Figure 7) are relatively similar to those of the CMIP5 GCMs shown in Figure A1.66 and A1.67 of the Annex 1 of the IPCC AR5 Report (IPCC, 2013), showing a decrease in dry season rainfall and no change in wet season rainfall. This provides some level of confidence that the CMIP3 GCM projections used here are still useful in the absence of the CMIP5 GCM projections at the time of the study.

The fact that downscaling produces a different projection to the GCMs has also been found elsewhere, such as in Australia (CSIRO and Bureau of Meteorology, 2015). The differences are understandable due to dissimilarities in modeling processes and methods in both the dynamical downscaling and host GCMs. For example, the CCAM downscaling uses an atmospheric model with its own model components, which can differ to those of the host GCMs, which simulate the atmosphere. In this regard, this study does not treat the downscaled projections as superior to the GCM projections, or vice versa. Instead, to cover all possible uncertainties, the projected changes from CCAM downscaling and host GCMs are both considered to represent plausible future projections.

Analysis of the combination of both the downscaled and host GCM data, totaling twelve simulations, projects a decline in Ampenan's dry season rainfall by around -1% (range +25% to -29%) and 3% (+8% to -30%) for the 2030s and 2050s, respectively. The wet season projected decline is about -4% (+7% to -14%) and -4% (+10% to -8%), respectively. For Sumbawa's dry season rainfall, the projected reduction is about -3% (+25% to -31%) and -6% (+7% to -35%) for the 2030s and 2050s, respectively. Meanwhile, for the wet season they are -4% (+13% to -13%) and -3% (+14% to -10%), respectively. Thus, the overall results suggest a potential small decrease in both seasons for both stations, but with some wide ranges.

5. Potential implications of rainfall change on the agriculture and water sectors

Agricultural practices in a given location are often strongly influenced by long-term mean climate conditions, and changes in either the mean or interannual variability can pose a major impediment to productivity (Gornall et al. 2010). This is particularly the case in NTB, where 41% of the agricultural area is rain-fed (BPS, 2012). Figure 8 shows modeled seasonal rainfall distribution in three different decadal periods. Overall, rainfall is projected to shift towards a lower mean during the dry season and little change during the wet season. Considering that there is a statistically significant positive correlation between paddy rice production and seasonal rainfall in NTB (Handoko and Hardjomidjojo 2009; Ripaldi et al. 2014), the change to a lower rainfall regime may lead to an overall reduction in average paddy production. Additionally, Figure 8 indicates that the maximum value of wet season rainfall distribution will moderately fall, which may subsequently have implications for water storage required for irrigation in the following dry season.

Rice is the staple food in NTB and is the primary crop. Farmers usually plant rice paddies two or three times a year in irrigated areas, but only once or twice per year in non-irrigated areas. The first growing period is generally around November to February, the second is March to June, while the third is July to October (MoE, 2010). Secondary crops such as corn and soybeans are also planted in the second and third growing periods. To illustrate the potential effect of changes in mean rainfall on each growing period, Figure 9 plots the mean seasonal cycle of rainfall in Ampenan currently and in the future (i.e. simulated) relative to local cropping periods. It must be noted that this plot is based on the projected values at monthly time steps, which differs to previous sections where the analyses are based on seasons (i.e. wet and dry). The mean rainfall amount for the first growing period is projected to fall from 956 mm in the 1990s (baseline) to 931 mm (range 695-1158 mm) by the 2030s, and to 929 mm (range 747-1075 mm) by the 2050s.

Crops need water for transpiration, and the amount of water required to meet this need ('crop water demand') during the growing period depends on many factors including crop type, local climate and soil condition. Crop water demand can be met through irrigation and/or rainfall. In this regard, comparing rainfall magnitude against water demand may indicate the irrigation needed for a given crop's growing period and hence provides a crude indication of potential impacts of projected rainfall change.

Water demand for several main crops (e.g. paddy rice, legumes, maize, chillies and tobacco) in Lombok has been calculated by McClymont et al. (2009), following the methodology described by Doorenbos and Pruitt (1977). According to McClymont et al. (2009), paddy water demand during the growing period in Lombok ranges from 950 to 1500 mm depending on soil type. Assuming that paddy water demand is 950 mm, the projected decline in rainfall in the first growing season (i.e. from 956 to 931 and 929 mm by the 2030s and 2050s, respectively) could increase irrigation water demand. If paddy water demand was at the highest end of the range at 1500 mm, this would result in an even greater deficit.

Using McClymont et al.'s (2009) water demand for other crops, it is estimated that the present deficit could also still occur during the second growing period of March-June (Figure 10). Overall, this might result in increased pressure on other water resources such as groundwater, and for high value crops such as chillies and tobacco during the dry season (McClymont et al. 2009). Since groundwater resources are also used for town and rural water supplies, increased agricultural demand might in turn intensify competition for this resource. Moerwanto (2011) suggests that the current water use index for NTB (defined as the ratio between water demand and water supply) is already critically high (i.e. more than 0.6). In the third growing period (July-October), mean rainfall is projected to remain unchanged (Figure 9), and hence the projected irrigation demand for all crops will remain at the baseline (Figure 10).

It is worth noting that the above estimates simply use current crop water demand values to calculate irrigation needs. However, the regional ambient temperatures in NTB are projected to increase (McGregor et al. this issue), potentially increasing evapotranspiration and intensifying the hydrological cycle (Huntington, 2006). The projected increase in temperature could elevate crop water demand, which in turn would result in an even greater water deficit for the first and second growing periods.

6. Discussion and conclusion

Livelihoods in NTB are predominantly dependent on agriculture (Butler et al. 2014), and agricultural production is highly dependent on rainfall and irrigation. Since almost half of NTB's agricultural area is rain-fed (BPS 2012), and 60% of irrigation infrastructure is estimated to be damaged (NTB Public Work Office, reported in sumbawabaratnews.com, 2 October 2012), any changes in rainfall quantities and/or variability will have a significant impact on livelihoods.

Information regarding historical and future rainfall has been generated using two rainfall stations as case studies. These two stations have the same monsoonal cycle typical of NTB Province, but they also show different long term means and variability. In the absence of wide spatial coverage of stations with long and good-quality rainfall data sets, results from this study can be generalized for NTB. Also, the overall methodology is transferable to other locations in NTB and elsewhere.

Our analysis on the observed rainfall data from Ampenan and Sumbawa rainfall stations indicate similar modes of variability with approximate periodicities of around 2-4, 5, 8, 11, and 40-50 years. The shorter periodicities seem to be associated with the ENSO phenomenon, and the results are consistent with the existing understanding that the association is best seen for the dry season and is less clear for the wet season. Overall, the results also indicate variation between the two locations (Ampenan and Sumbawa) and hence justify the need for regional simulations with finer-scale resolutions in NTB.

Previous rainfall projections for Lombok were carried out by the Lombok Vulnerability Assessment, and were developed using the mean ensemble of five CMIP3 GCMs and three emission scenarios (MoE, 2010). MoE's projections suggested that rainfall will not largely change by 2030, but will decline by 2080 particularly during the transition months (i.e. March-April) and early wet season months (i.e. October–November). By providing recent regional climate simulations at 14 km spatial resolution (McGregor et al. this issue), this study improves these projections and extends the analysis to include Sumbawa island.

Our results suggest that the observed modes of variability will continue in the rest of this century. The models indicate periodicities of around 2-3, 5-8, 10-14, 20 and 60 years. Thus, future changes in rainfall may be expected. Whether or not the expected changes are caused by the long periodicity within the model and/or by the sensitivity of the local climate to global warming is beyond the scope of this study.

Overall, rainfall is projected to slightly decline (-1% to -6%, depending on season and location) even by 2030 and 2050, although there is a range of uncertainty attached to this. For example, Sumbawa's dry season rainfall by the 2050s is projected to decrease by -6% according to the median of multi-models ensemble (Section 4.2.). However, the maximum-minimum range of projection is +7% to -35%, implying that a 35% decrease (or a 7% increase) in future rainfall is equally plausible. Therefore, it is very important to consider all uncertainties when utilizing climate projections in subsequent impact assessments and adaptation planning for agriculture, irrigation and livelihoods (Butler et al. this issue b).

The results also indicate that rainfall change will potentially impact the first cropping period for paddy rice (November-March), and rainfall may continue to be insufficient to meet water demand for many crops in the second growing season of March-June, when high value crops such as chillies and tobacco are grown. The Lombok Vulnerability Assessment (MoE, 2010) also noted that declining rainfall could result in the failure of crop planting, but our analysis suggests that these impacts may occur sooner than previously suggested. This also implies that there will potentially be an increase in demand for irrigation infrastructure and groundwater in the near future. This has serious implications for decision-making because once built, such infrastructural investments are not easily reversible and could be 'mal-adaptive' (Butler et al. this issue b, Wise et al. this issue). However, further impact assessments are required which can also model the potential impact of other climate variables (e.g. temperature and evaporation), plus additional variables such as human population growth, the standard of irrigation infrastructure and alternative agricultural practices. The Assets Drivers Well-being Interaction Matrix, which was developed to address such multiple issues, provides a tool appropriate for participatory analysis of such impacts on livelihoods (Skewes et al. this issue).

The presentation of complex and abstract climate information to multiple stakeholders, many of whom have local worldviews and experiences and a limited understanding of science, is a major challenge for adaptation planning processes (Butler et al. 2014; Butler et al. 2015). Hence one consideration for this study was which data to present on past and future projected rainfall variability, plus the inherent uncertainties in our modeling. For this purpose we primarily presented the rainfall projections relative to the three cropping periods (Figure 9). This proved effective for three reasons. First, the graph visually shows current monthly average rainfall, which is locally relevant and easily understood. Second, the potential change in monthly rainfall relative to current conditions is clearly discernible. Third, the range of uncertainty (presented as the shaded area between the maximum and minimum values) is easily visible, and visually indicates the potentially wide variations in projected rainfall, which is important when considering future scenarios (Butler et al. this issue b).

This study is a first step towards enhancing our understanding of rainfall variability in NTB, but only examines seasonal rainfall. At the time of the study, high quality daily rainfall observational data were not available, and consequently we could not examine other critical characteristics such as the onset and withdrawal of the wet season, and hence changes in the length of cropping periods. The DATACLIM project involving BMKG is currently underway focusing on Indonesian data restoration, data archival improvement, quality control, and dissemination (E. Aldrian, personal communication 2014). Once these daily data are available and accessible it may be possible to undertake these more detailed analyses, and input the results into adaptation planning.

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Table 1. Observed seasonal rainfall periodicities, which are significant at 95% confidence level, for Ampenan and Sumbawa. Values are rounded, and those written in bold are significant at 99% confidence level.

Station	Periodicities (years)
Ampenan	Dry season : **40**, **5**, 3
	Wet season: **50**, **11**, 4, 3, 2
Sumbawa	Dry season: **5**
	Wet season: **50**, 8, 4, 3

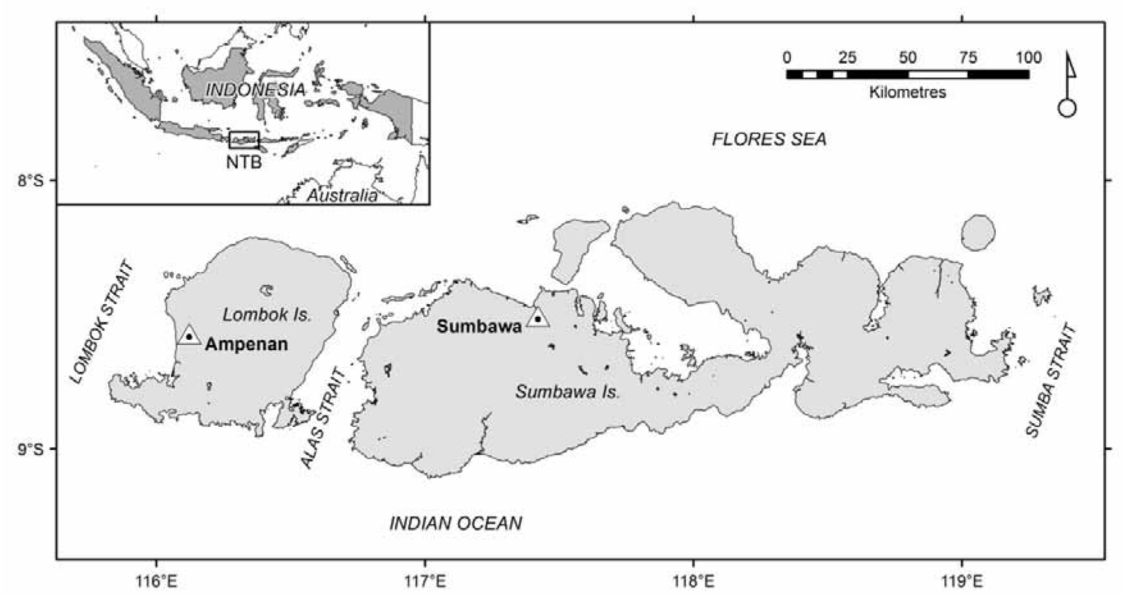

Figure 1. NTB Province, Indonesia, showing the locations of Ampenan and Sumbawa rainfall stations.

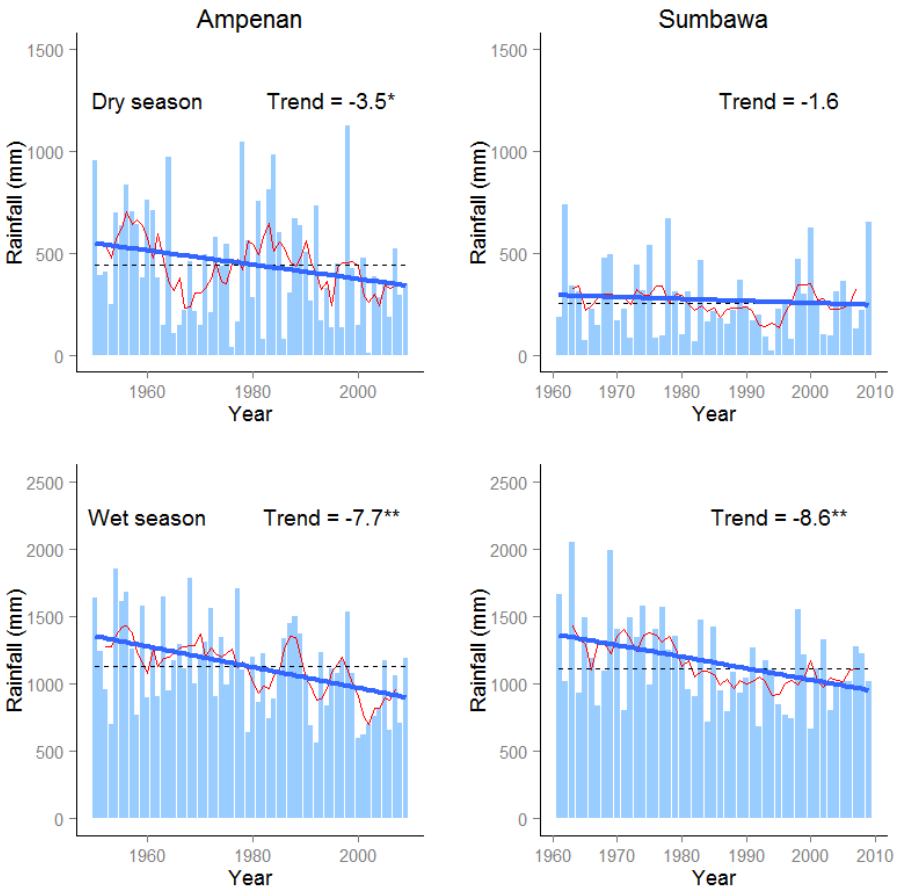

Figure 2 Observed seasonal rainfall in Ampenan and Sumbawa, along with the 1971-2000 mean (dashed lines), 5-year moving average (red lines), and linear trend (thick-blue lines). Trend is in mm per year. A * shows that trend is significant at p<0.1, while the ** shows that trend is significant at p<0.01.

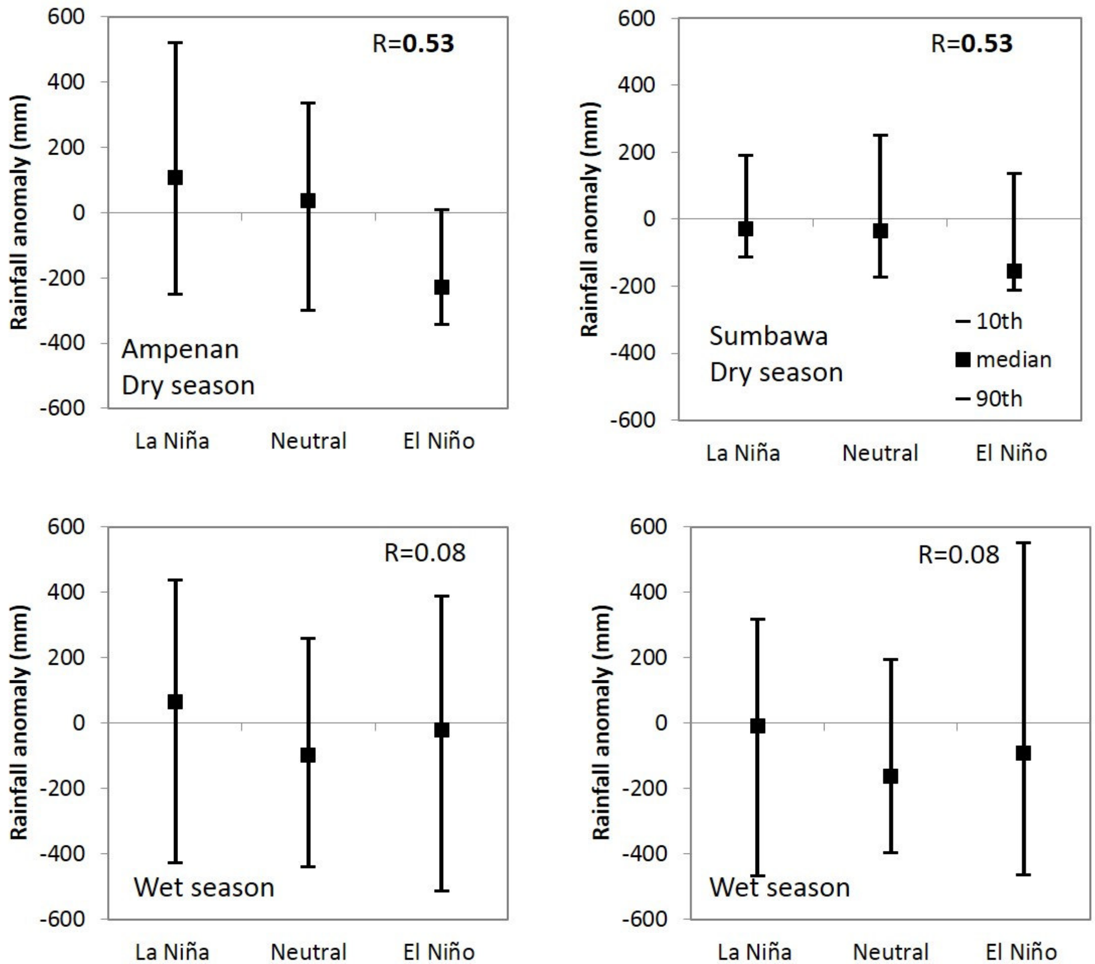

Figure 3 Box plot of seasonal rainfall anomaly for different ENSO event (El Niño, La Niña and Neutral). The definition of ENSO-event is based on the long paddock (http://www.longpaddock.qld.gov.au/). Pearson's correlation coefficient (R) between detrended seasonal rainfall and detrended Troup Southern Oscillation Index (SOI) is also provided (values written in bold are significant at the 95% confidence level).

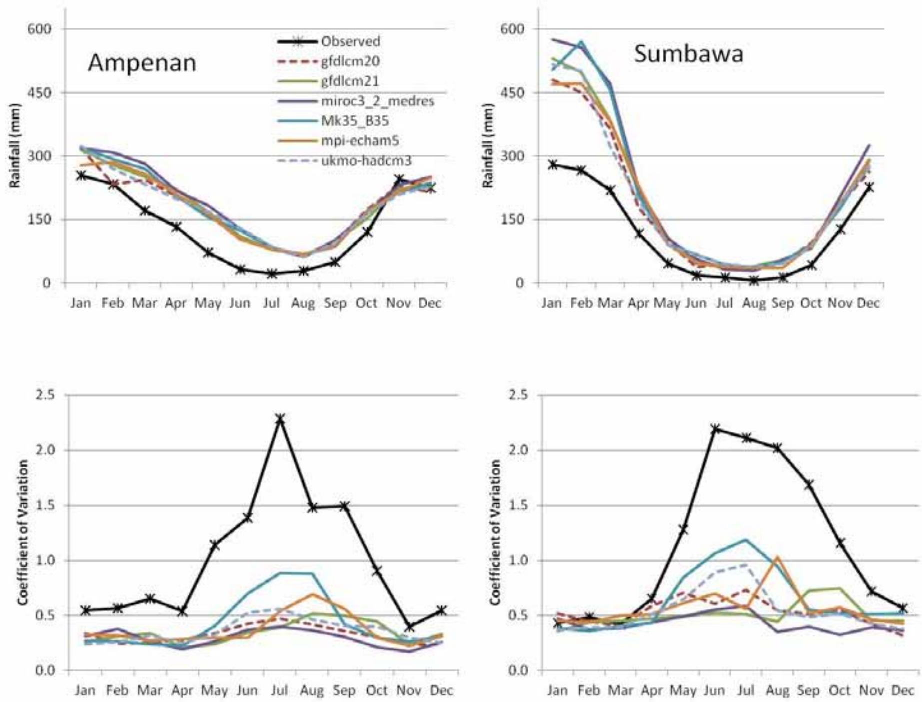

Figure 4. Observed and simulated long-term mean (top) and coefficient of variation (bottom) of monthly rainfall for 1971-2000. The coefficient of variation is defined as the ratio of the standard deviation to the mean.

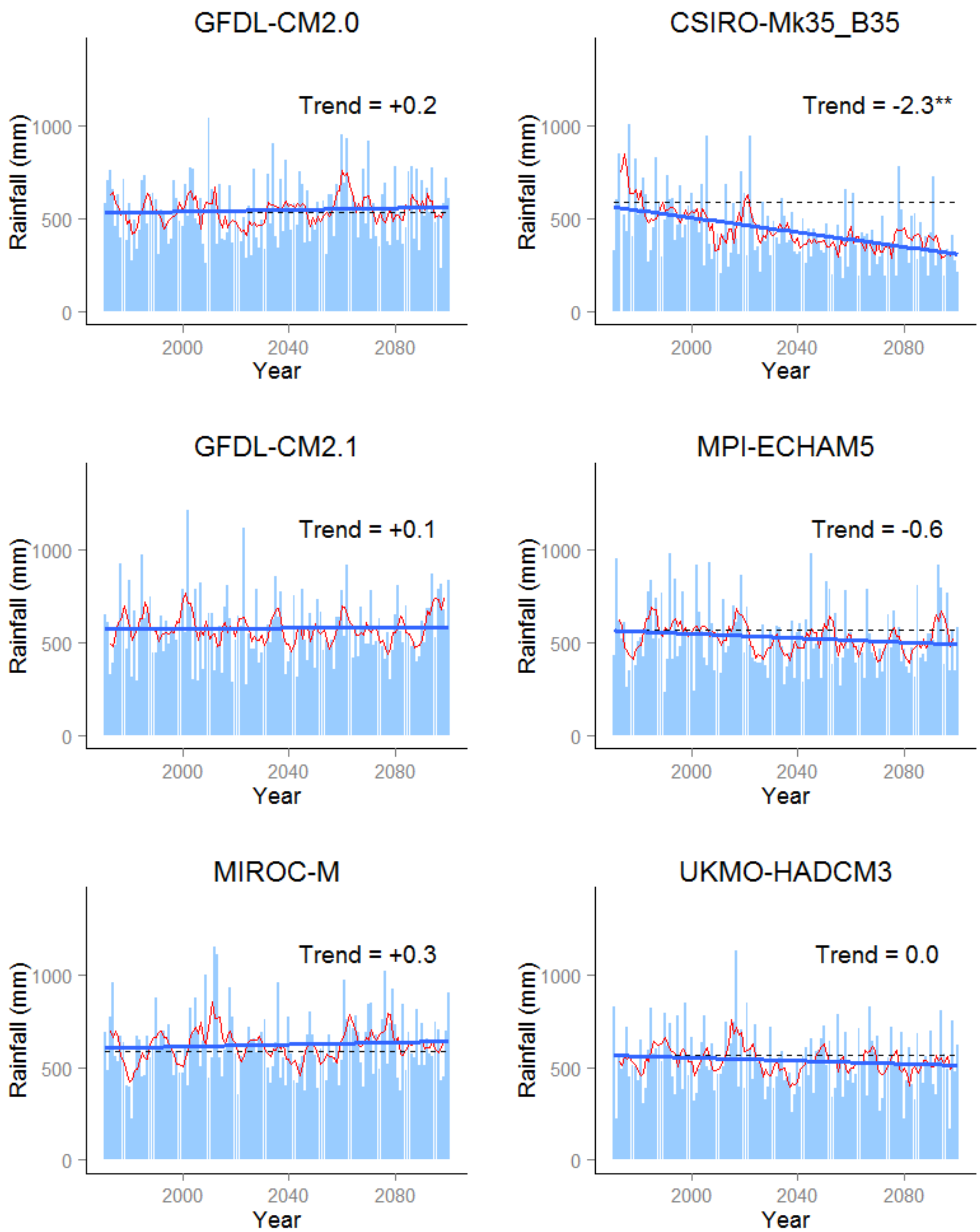

Figure 5. Dry season rainfall from six downscaled model simulations in Sumbawa, along with the 1971-2000 mean (dashed lines), 5-year moving average (red lines), and linear trends (blue lines). Trend is in mm per year. The ** shows that trend is significant at p<0.01

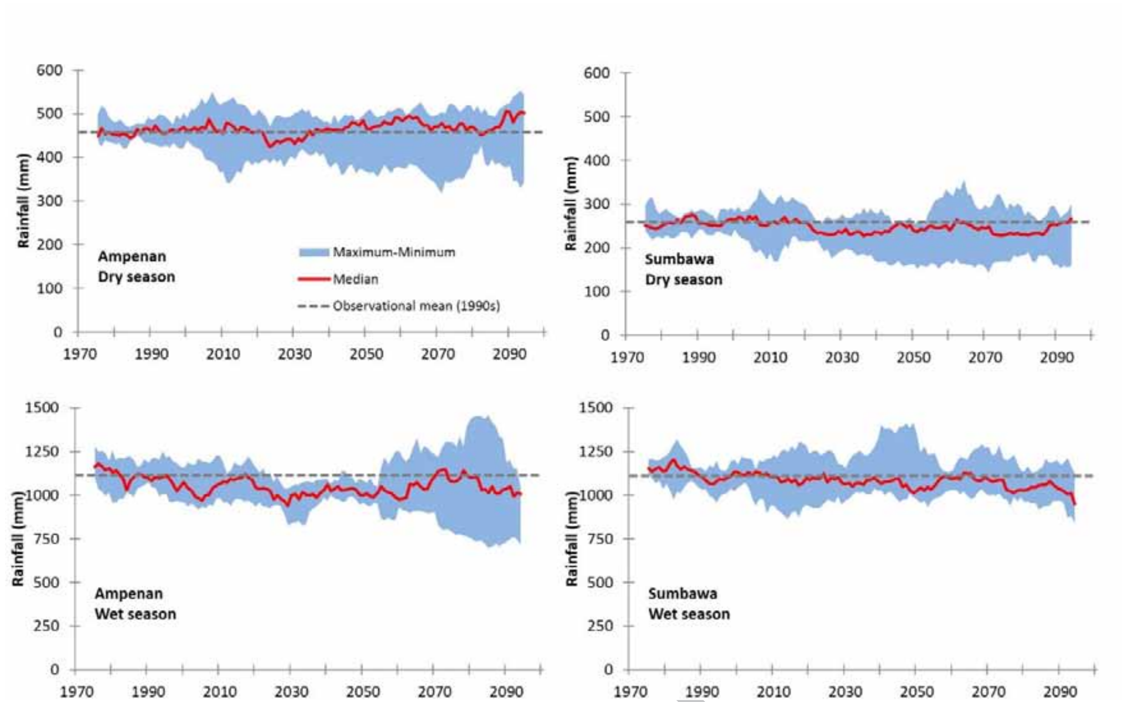

Figure 6 11-years moving average of the six ensemble simulated rainfall for 1971-2100. Red lines denote the multi-model median, while the blue ranges indicate the maximum and minimum rainfall values. Dashed horizontal lines show the observational mean rainfall in 1971-2000.

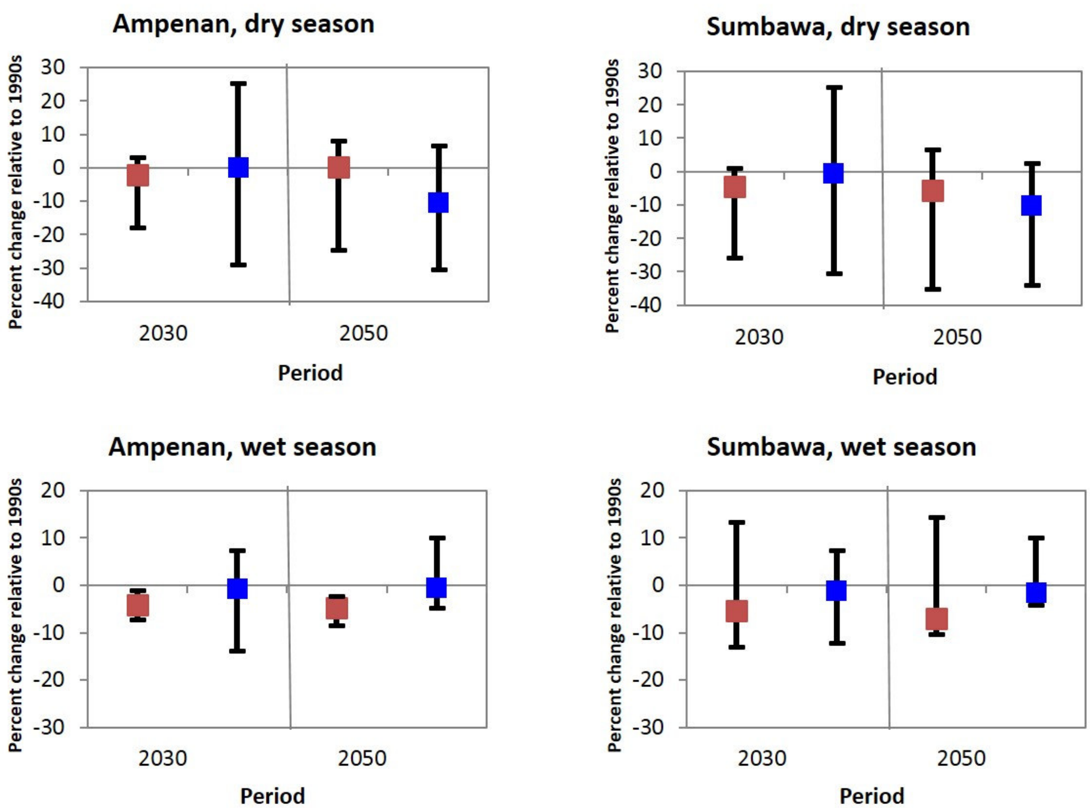

Figure 7 Percentage changes in rainfall for future periods relative to 1990s period based on an ensemble of six downscaling simulations (red), and six host-GCMs (blue). The bars represent the multi-model maximum and minimum values, while the middle symbols are the median. The 1990s period is 1971-2000; 2030s is 2015-2046; and 2050s is 2045-2066.

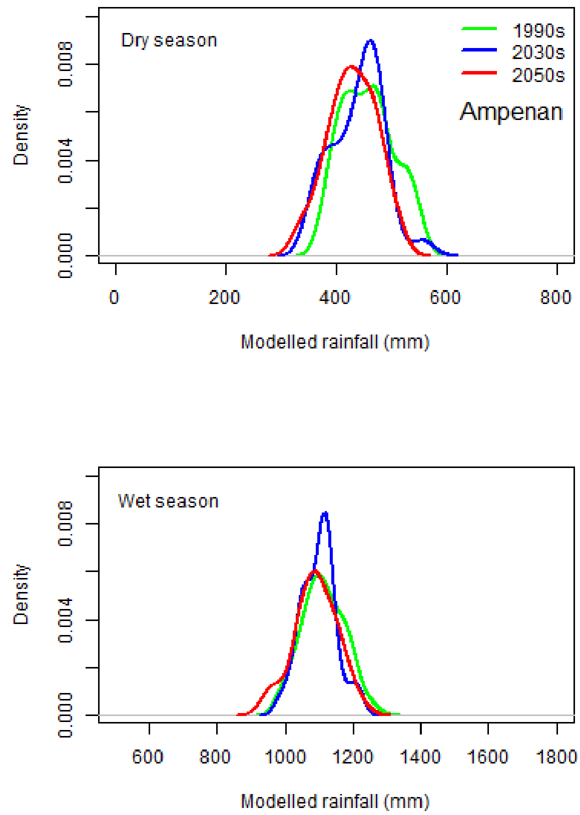

Figure 8 Rainfall distribution of the multi-models ensemble for Ampenan for three different periods (1990s is 1971-2000; 2030s is 2015-2046; and 2050s is 2045-2066.). The multi-model ensemble includes six downscaling simulations and six host-GCMs simulations, totalling to 12 simulations data.

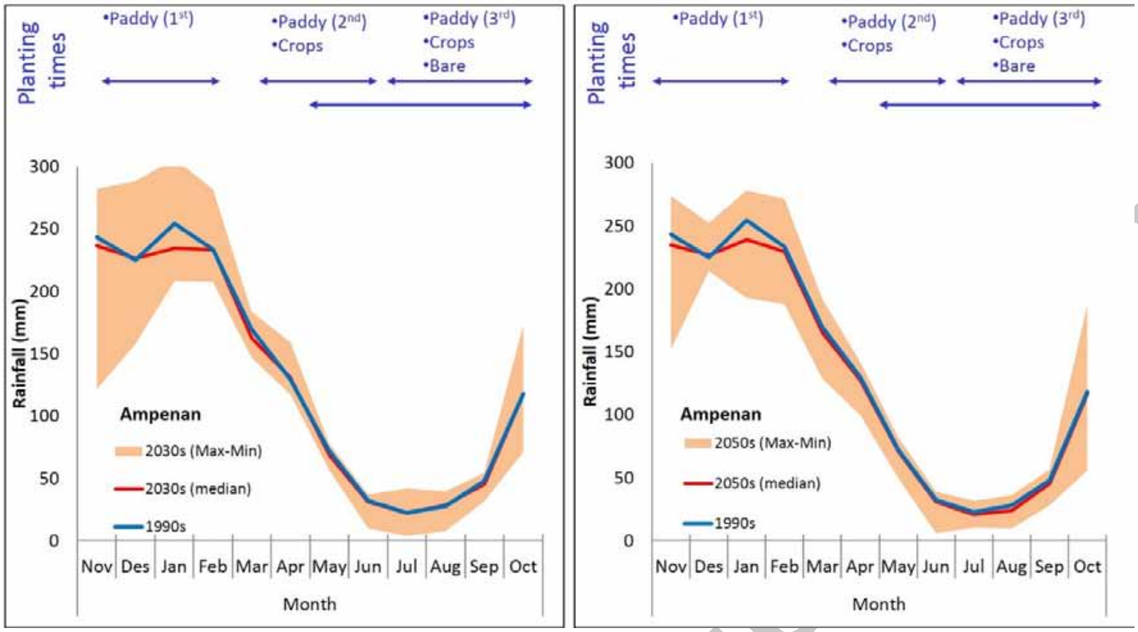

Figure 9 Observed (1990s) and projected (2030s and 2050s) mean monthly rainfall in Ampenan, relative to current growing periods. The range of projected values is illustrated by the multi-model median (red lines), and maximum and minimum rainfall values (orange shades). The multi-model ensemble includes six downscaling and six host-GCMs simulations, totalling to 12 simulations data.

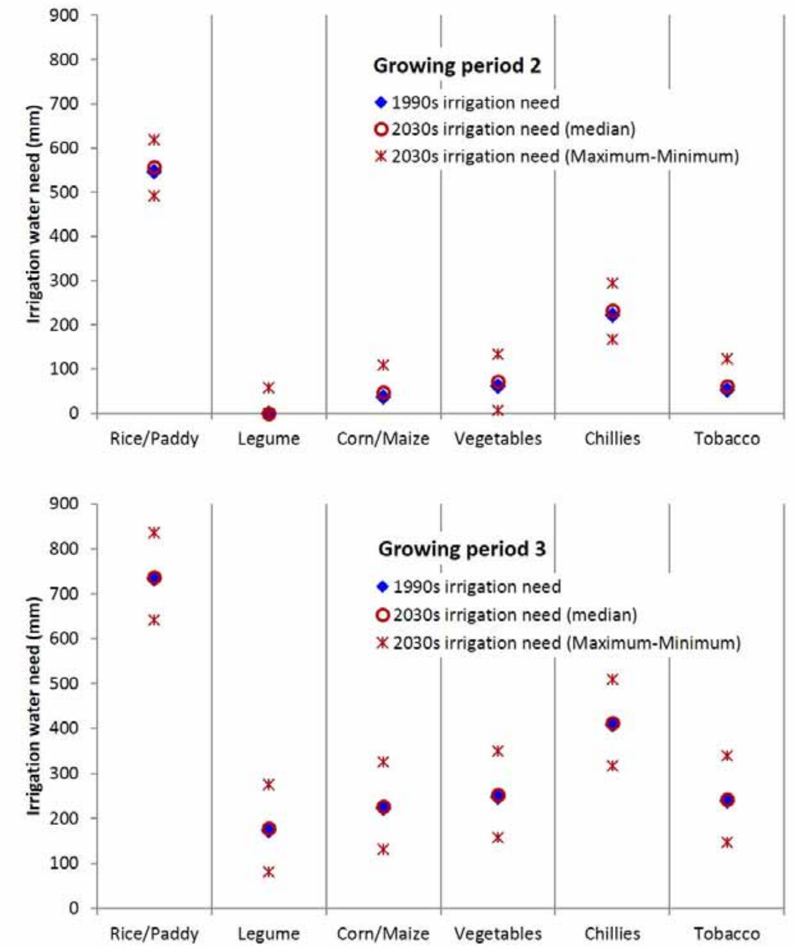

Figure 10 Potential irrigation water need to meet water demand for different crops in the second growing period (March-June) and third growing period (July-October) in Ampenan for the current (1990s) and the future (2030s). Irrigation need is defined as the gap between the crop water demand and the projected amount of rainfall. Range of estimated values denotes results informed by the multi-model median (red circles) and maximum-minimum (red crosses) projections. The multi-model ensemble includes six downscaling and six host-GCMs simulations. The NTB current crop water demand values are obtained from McClymonth et al. 2009. In this estimate, paddy water demand is defined as 950 mm. At the time of the study, projected water demand values are not available – this figure uses the current water demand values to calculate irrigation need in the future.