RCCAP | REGIONAL CLIMATE CONSORTIUM FOR ASIA AND THE PACIFIC

Developing and Applying Climate Information for Supporting Adaptation in South East Asia

Indonesian Case Study: Climate Projections and Drought Hazard Assessments in East Java Province

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CONTEXT

The Asian Development Bank (ADB) has seen that use of climate services to support climate adaptation in Asia and the Pacific, in particular, is challenged by limited reliable climate information, insufficient capacity to interpret and use of climate information, and limited technical and financial resources.

To address this challenge, the ADB supported a technical assistance (TA) project, TA-8359 REG: Regional Climate Projections Consortium and Data Facility for Asia and the Pacific. This TA aims to:

i. provide users with advice on what climate information is available, where, and how to use it;
ii. present guidelines for developing and using a range of available climate information to support climate adaption; and
iii. deliver a range of knowledge products that may be used for informing policy decisions and planning for climate adaptation.

About this case study

Purpose

The guideline developed in this TA outlines a 10-step approach to using climate data to develop climate information. The guideline is available on the RCCAP portal at www.rccap.org.

This case study complements the guideline by illustrating how climate change information can be developed and used in an impact and vulnerability assessment. It also shows how to transform the assessment results into knowledge products that are more digestible to the next- and/or end- users (e.g. planners, managers, policy makers, etc.).

Background

This case study was identified and planned at the RCCDF project inception workshop in Chiang Mai (Thailand) in May 2015 and the first regional workshop attended by various stakeholders in Bali (Indonesia) in July 2015.

At the inception workshop, it was decided that case studies should be real cases if possible, and simple enough to complete within available resources, and be demonstrated through a one-week workshop.

The case study develops climate projections and drought hazard assessment for the East Java Province of Indonesia. The case is a continuation of previous work in the Study of Integration of Climate Change Adaptation into Spatial Planning Policies conducted collaboratively by the Ministry of Agrarian and Spatial Planning (MASP), the Japan International Cooperation Agency (JICA), and researchers from the Climate Change Centre – Institute of Technology Bandung (CCC-ITB; see Ministry of Public Works and Japan International Cooperation Agency, 2015a; 2015b).

Climate risk assessment for spatial planning policies requires climate projections and several climate hazard assessments including drought, landslide, flood and coastal inundation (see Figure 2). Owing to resource limitations, this case study is only concerned with climate projections and drought hazard assessment.

Upon completion, the case study was demonstrated and thought in a training workshop held in Yogyakarta, Indonesia, 28–31 March 2016. The training gave participants the opportunity to see how the step-by-step guideline could be applied, and was attended by 29 representatives of government departments, academia, research providers, and international experts. All training materials are available at www.rccap.org.

Case study team

The team consists of three Indonesian specialists of the TA-8359 REG. They are M.S. Fitriyanto, M.Sc. (IAV Specialist); Dr. Agus Supangat, DEA (Knowledge Management Specialist); and M. Rizky Ramadhan, MT (Climate Change Specialist), with the assistance of Faiz R Fajary, ST. The team also engaged two independent resource persons from the Climate Chenge Center ITB (Dr. Tri Wahyu Hadi and M. Ridlo Syahputra, MT.). All played an important role in the previous work of the Ministry of Public Works and Japan International Cooperation Agency (2015a; 2015b) and hence they have the right capability and experience needed for the success of the case study.

About this document

Audience

This document is targeted at professionals who have some background knowledge of climate adaptation. Examples include researchers, university lecturers and students, consultants, sectoral planners, and personnel of meteorological and climatological departments whose mandates may include provision of climate information services.

Structure

This document has three sections. This first section provides context for the case study and this report. The second presents the development of climate change information within this context, and is structured in line with the 10 steps outlined in the guideline. The final section provides a synthesis. Any references and data used are provided in the reference list and appendix, respectively. A more detailed module on various technical calculations is provided in a separate training module (Fitriyanto et al., 2016) available at www.rccap.org.

CLIMATE CHANGE INFORMATION DEVELOPMENT

1 Define the requirements of the study

Identifying the objective and scoping out the case study approach and requirements clarifies the information and resources required, and provides an operational framework to guide decisions along the way.

The case study objective and requirements were identified through a number of engagements with relevant stakeholders. The key stakeholders are the Ministry of Agrarian and Spatial Planning and the Local Government of East Java Province. Representatives from these institutions were invited and engaged through the first regional workshop in Bali (Indonesia) in July 2015, and the capacity building workshop in Yogyakarta (Indonesia) in March 2016.

1.1 Study objectives

As previously mentioned, climate projections and drought hazard knowledge are among the key information required for mainstreaming climate change risk consideration into spatial planning policy in Indonesia (Ministry of Public Works and Japan International Cooperation Agency, 2015a; 2015b).

The purpose of this case study is to demonstrate the development of climate projections for drought hazard assessment.

1.2 Scope

The case study was conducted for the East Java Province (Figure 1), which is one of the major rice producing regions in Indonesia. Drought is one of the hazards likely to impact some agricultural lands over the province. As such, results of this study can be used to manage agricultural lands in the future, for instance, by choosing the right adaptation options considering climate change, while also considering balanced use of these lands for other crops, for conservation, and for human settlements.

Figure 1. Case Study Areas of the East Java Province (Lat 9.125 S – 5.875 S; Lon 110.125 E – 115.125 E)

The assessment focusses on the frequency of drought based on two drought indices: the Standardized Precipitation Index (SPI) at 3- and 6-month scales, and the Dry Spell (number of no-rain days during wet seasons). Both indices required rainfall data (daily, monthly and seasonal) as input.

Rainfall climatology and drought frequencies for two different time periods are assessed. The baseline period is 1981–2010. The selection was determined based on data availabilities, particularly the merged TRMM-and APHRODITE datasets. The projection period is 2011–2040. This period is consistent with the spatial planning timeframe (2011–2031) for which the assessment results can be used. These periods are also the same to those used in the recent study conducted by the Ministry of Public Works and Japan International Cooperation Agency (2015a; 2015b).

1.3 Methodology

1.3.1 The Indonesian Climate Change Risk and Adaptation Assessment

The Climate Change Risk and Adaptation Assessment (CCRAA) approach (Figure 2), developed by the Ministry of Public Works and Japan International Cooperation Agency (2015a; 2015b), has been recommended as a guideline for formulating climate change adaptation for spatial planning in Indonesia.

The original CCRAA was developed by the Ministry of Environment in 2012 aimed to formulate climate change adaptation for development (sectoral) planning. The guideline was recently enacted as the Regulation of Ministry of Environment and Forestry of Number P.33/Menlhk/ Setjen/Kum.1/3/2016 about the Guideline of Development of Actions on Climate Change Adaptation (Ministry of Environment and Forestry, 2016).

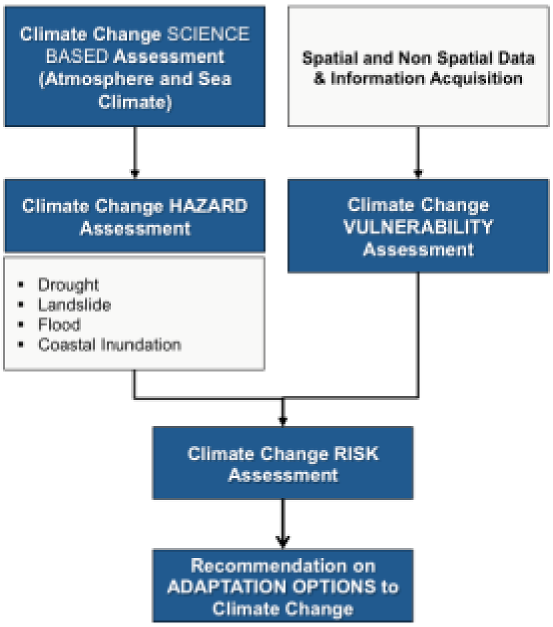


Figure 2. Framework of the Climate Change Risk and Adaptation Assessment (CCRAA)

The CCRAA for the spatial planning sector in Indonesia requires information about several types of hazards, including drought and flood. This case study focuses on drought hazard only thus the result may contribute to the overall process of the CCRAA. Subsequently, the results of a CCRAA can be integrated into two steps of a planning cycle: (1) spatial planning process and (2) review/evaluation of the spatial plan (Figure 3). Output of the spatial planning step is a draft of spatial plan which will be enacted to be a law product in accordance to the hierarchy of the spatial plan itself.

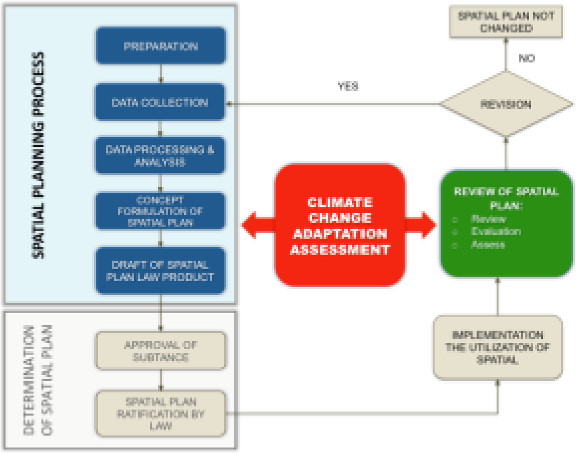


Figure 3. Conceptual representation of the Integration of Climate Change Adaptation into Spatial Planning

1.3.2 Method for Drought Hazard Assessment

Assessment of meteorological drought hazard is conducted by mapping a meteorological drought index for both the baseline and projection periods. The drought measure is the Drought Hazard Index (DHI), which represents the severity, frequency, and duration as the drought characteristics (Ministry of Public Works and Japan International Cooperation Agency, 2015b). The DHI in this case study is governed by a combination of several rainfall based indices.

A major indicator is the Standardized Precipitation Index (SPI; McKee et al., 1993). Advantages of this method are that it is applicable to both wet and dry climatic condition regardless of location, it is computationally simple, and it can be developed in different time scales. The SPI is, in principle, determined by normalizing the long-term precipitation data for a given station for a desired period or timescale, after it has been fitted to a probability density function. Negative values indicate less than median precipitation and represent drought conditions with categories listed in Table 1. The drought starts when the SPI value is equal to or below –1.0 and ends when the value becomes positive.

Table 1. SPI values determine the drought categories (McKee et al., 1993)

SPI VALUES	DROUGHT CATEGORY
–0,99 to 0,99	*Near normal*
–1,00 to –1,49	*Moderately dry*
–1,50 to –1,99	*Severely dry*
Less than –2,00	*Extremely dry*

As guided by the World Meteorological Organization (2012), a map of 1-month SPI is very similar to one displaying the percentage of normal precipitation for one month. It is actually a more accurate representation of monthly precipitation as the distribution has been normalized. In general, a particular-months-timescale SPI provides a comparison of the precipitation over the particular consecutive months with the precipitation totals from the same particular consecutive months during all the previous years of available data (see Table 2).

It is important to compare a short timescale SPI with any of the longer ones. A relatively normal or even a wet short period could occur in the middle of a longer-term drought that would only be visible over a long period. Comparing to the longer timescales could prevent misinterpretation that a drought might be over when in fact it would just a temporary wet period. Continuous and persistent drought monitoring is significant to determine when droughts begin and end. Note that the SPI maps might be updated at the end of each month.

Table 2. Interpretation of SPI According to Its Time Scale (World Meteorological Organization, 2012)

TIME SCALE OF SPI	INTERPRETATION
1-month SPI (SPI-1)	It reflects relatively short-term conditions, hence, its application can be related closely with **short-term soil moisture and crop stress, especially during the growing season**.
3-month SPI (SPI-3)	A 3-month SPI reflects short-and medium-term moisture conditions and provides **a seasonal estimation of precipitation**. In primary agricultural regions, it might be more applicable in highlighting **available moisture conditions** than some other slow-responding hydrological indices.
6-month SPI (SPI-6)	The 6-month SPI indicates medium-term trends in precipitation. A 6-month SPI can be very effective in showing **the precipitation over distinct seasons**. Information from the SPI may also indicate to **anomalous streamflows and reservoir levels**, depending on the region and time of year.
9-month SPI (SPI-9)	This SPI provides an indication of inter-seasonal precipitation patterns over a medium time scale. Droughts usually take a season or more to develop. Its values below 1.5 for these time scales are usually a good indication that fairly significant dryness impacts are occurring in **agriculture** and may be showing up in other sectors as well.
12-month up to 24-month SPI (SPI-12 up to SPI-24)	Because these time scales are the cumulative result of shorter periods that may be above or below normal, the longer SPIs tend toward zero unless a distinctive wet or dry trend is taking place. The SPI at these time scales reflects long-term precipitation patterns. They are probably tied to **streamflows, reservoir levels, and even ground-water levels at the longer time scales**.

We should choose one or several timescales of SPI that are suitable to the case study of East Java Province. In developing a spatial plan, this province should develop climate change adaptation applied to its large agricultural lands as it has highest yields of agricultural products, especially rice, in Indonesia.

To get information on the duration or time scale of the drought, comparisons were made between the drought occurrences as identified by SPI-3 downstream of Bengawan Solo Rivershed over the province and the real drought occurrences recorded by the National Agency of Disaster Mitigation (see Table 3).

Table 3. Historical/Recorded Drought and Drought Occurrences Identified by SPI-3 in the East Java Province (Source: Indonesian Ministry of Agrarian and Spatial Planning and Japan International Cooperation Agency, 2015b)

YEAR	DROUGHT EVENTS IDENTIFIED BY SPI-3		DROUGHT EVENTS IN HISTORICAL RECORD
	ONSET	DURATION (MONTHS)	
2003	September	1	May-2003
			Sep-2003
2004	-	-	May-2004
2005	February	4	Jan-2005
			Feb-2005
			May-2005
			Sep-2005
			Nov-2005
2006	August	5	Oct-2006
2007	January	6	Jan-2007
			Jun-2007
			Jul-2007

Table 3 shows that most drought events in historical record are related to four months or longer consecutive SPI-3 of less than –1.5 (severely dry). In this case, we also believe that SPI-6 also contributes to severity of drought on agricultural lands, especially on plantation farms that are cultured in many places in this province. Besides, the drought severity that might be impacted on numerous human settlements over the province could also be indicated by a dry-spell indicator: the no-rain occurrences in 15 consecutive days or longer during the wet or rainy season (December–January–February).

Based on these analyses, the Drought Hazard Index (DHI) is determined by the following three indicators:

- Dry Spell, 15 or more consecutive no-rain days during wet season (Dec-Jan-Feb)
- SPI-3, four or more months consecutive severely dry SPI-3 (i.e SPI <= –1.5)
- SPI-6, four or more months consecutive severely dry SPI-6 (i.e SPI <= –1.5)

The weight (W) of the DHI is determined based on Table 4.

Table 4. Weight values of the three indicators of DHI

INDICATOR	WEIGHT
Dry Spell	1/6
SPI-3	1/3
SPI-6	1/2

The ratings (R) are determined based on normalization of occurrence frequency of each indicator during either baseline or projection period, so that the rating will have values between 0 to 1.

The DHI can be then calculated by a weighted-sum formula:

DHI = (W1 x R1) + (W2 x R2) + (W3 x R3)

The calculated DHI is then classified according to five hazard levels (Table 5).

Table 5. Classification of the five DHI levels

DHI VALUE	CODE	DHI LEVEL
0 – 0.2	1	Very Low
0.2 – 0.4	2	Low
0.4 – 0.6	3	Moderate
0.6 – 0.8	4	High
0.8 – 1	5	Very High

2 Collect and assess observed climate data

The baseline climate data are a mix of station datasets as well as APHRODITE and TRMM gridded observed datasets (see Appendix).

The station datasets (Table 6 and Table 7) were obtained from:

1. The Southeast Asian Climate Assessment & Dataset (SACA&D) project by the Agency for Meteorology, Climatology, and Geophysics (BMKG);
2. The Research and Development Center on Water Resources (PUSAIR) of the Ministry of Public Works.

The time span of TRMM data is limited (1998–2011). To extend these data over a climatic period, TRMM data were merged with APHRODITE data which have longer time span (1981–2007), producing a total time span of 1981–2011. However, the APHRODITE data tended to have a negative bias (i.e. underestimate) of rainfall compared with the TRMM data. To reduce this bias, APHRODITE data was corrected using quantile-based bias correction.

Table 6. Brief Description of Station (Observational) Rainfall Data Obtained from SACA&D

NO	STATION NAME	LAT.	LON.	START	END
1	Banyuwangi	-8.2200	114.3800	1961-01-01	2014-12-31
2	Dadapan	-8.2500	114.3167	1961-01-01	2014-12-31
3	Juanda	-7.3700	112.7700	1971-01-01	2014-12-31
4	Kalianget	-7.0500	113.9700	1983-06-01	2014-12-31
5	Malang	-7.9667	112.7000	1973-02-01	2014-12-31
6	Perak	-7.0000	112.0000	1960-01-10	2014-12-31

Table 7. Brief Description of Station (Observational) Daily Rainfall Data Obtained from PUSAIR

NO	STATION NAME	LAT.	LON.	START	END
1	Semarang	-6.9800	110.3800	1957-01-01	2013-12-31
2	Surabaya	-7.2200	112.7200	1949-01-01	2013-12-31
3	Duduk Sampeyan	-7.1653	112.5205	1981-01-01	2011-12-31
4	Gantiwarno	-7.7653	110.5585	1989-01-01	2012-12-31
5	Gondang	-7.3964	111.8491	1979-01-01	2011-12-31
6	Jati Blimbing	-7.4077	112.4542	1982-01-01	2011-12-31
7	Karang Nongko	-7.4199	111.8127	1979-01-01	2011-12-31
8	Tambak Ombo	-7.1292	111.9555	1981-01-01	2011-12-31
9	Tegalrejo	-6.9109	112.0053	1981-01-01	2011-12-31
10	Ngujung	-7.8522	112.5381	1971-01-01	2010-12-31
11	Dau	-7.9225	112.5872	1971-01-01	2010-12-31
12	Lawang	-7.8044	112.6983	1971-01-01	2010-12-31

3 Select representative concentration pathways

Analyses are based on climate projections associated with the IPCC AR5 RCP4.5 and RCP8.5 greenhouse gas concentration levels, representing moderate and high levels of greenhouse gas emissions. According to the previous work of the Ministry of Public Works and Japan International Cooperation Agency (2015a), RCP4.5 was judged to sufficiently represent the moderate condition in Indonesia (especially the rainfall parameter) that is comparable to the IPCC AR4 based SRES A1B scenario, which had been used in previous CCRAA (Ministry of Environment, 2012).

4 Find relevant climate model data

This case study found some statistical and dynamical downscaled outputs:

- Statistically downscaled data is from three GCMs (MIROC5, Nor-ESM1-M, IPSL-CM5A-MR) which were combined with the baseline climate data. The statistical downscaling simulations were conducted by the study team by extending a methodology that has been developed through the previous work of the Ministry of Public Works and Japan International Cooperation Agency (2015a). The extensions were made to include observed data from two additional rainfall stations (i.e. Semarang and Surabaya) into the statistical model development and to conduct subsequent simulation runs for this case study and for training module development (Fitriyanto et al., 2016).
- Dynamically downscaled data is from six GCMs (ACCESS1.0, CCSM4, CNRM-CM5, GFDL-CM3, MPI-ESM-LR, and NorESM1-M) using CSIRO's Conformal Cubic Atmospheric Model (CCAM). Simulations were performed globally at 50 km resolution using bias and variance correct sea surface temperatures generated by the above GCMs from 1971 to 2100 forced using two scenarios: RCP 4.5 and RCP 8.5.

4.1 Statistical Downscaling Method and Data Required

Statistical downscaling is useful to resolve sub-synoptic features using statistical relationships between observed coarse-scale (the predictors) and local (the predictand) climate. The method has some advantages. For example, it is computationally cheap, and has the ability to create mass ensembles, downscale to point locations, and easily compare results to observed climate. However, there are also several disadvantages, including that it assumes stationarity in coarse-local relationships, and neglects local feedback processes such as snow albedo, soil moisture and cloud cover. There are many methods available for statistical downscaling. The Constructed Analogues (CA) method was used in this study due to its capability of resolving problems of representing extreme climate parameter values or events better than other methods, such as the simple delta and regression methods (Hidalgo, et.al., 2008; Ministry of Public Works and Japan International Cooperation Agency, 2015a).

The CA method comprises two processes:

1. Diagnosis. This is a process of choosing a subset of predictor analogue patterns from available database to find a subset of suitable analogues. In this process, a predictor pattern in a target time is matched to predictor patterns in database. Empirical Orthogonal Function (EOF) method is used to reduce degree of freedom (d.o.f) of predictor fields.

For each target time *t*, a subset of predictor analogue in the database and the matched predictant are chosen based on similarity value.

2. Prognosis. This is a process which analogue is formed from predictant at target time based on a subset of selected predictor analogue. In this study, the formation of constructed analogue from predictand at a target time t is calculated based on weighted average of predictors (Fernández and Sáenz, 2003).

Figure 4 is a simple illustration of the diagnosis and prognosis processes.

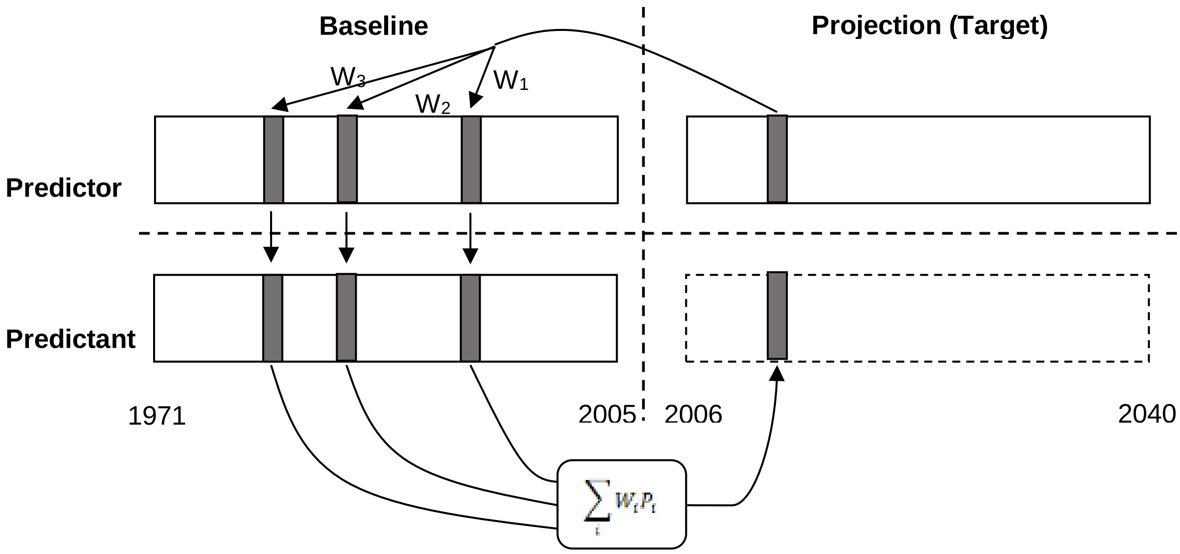


Figure 4. Figure 4: Illustration of diagnosis (analogue searching) and prognosis process for constructed analogue. In this illustration, a weighted averaging method is employed in the prognosis process (edited from Fernández and Sáenz, 2003)

In this study, stream function (ψ) and velocity potential (χ) at level 850 mb are used as predictors. Both functions are atmospheric circulation quantities representing rotational and divergence components of horizontal wind field, respectively. Those variables ψ and χ are calculated from zonal (u) and meridonal (v) wind. Besides that, the CA method is applied for five windows, representing three domains of defined Asia-Australia monsoon index, namely: AUSMI (Australian Monsoon Index), WNPMI (Western North Pacific Monsoon Index) 1, WNPMI 2, WYMI (Webster-Yang Monsoon Index) 1, and WYMI 2 (Figure 5). Furthermore, the CA method is applied for three GCMs (Nor-ESM1-M, MIROC5, and IPSL-CM5A-MR) for climate change scenario RCP4.5.

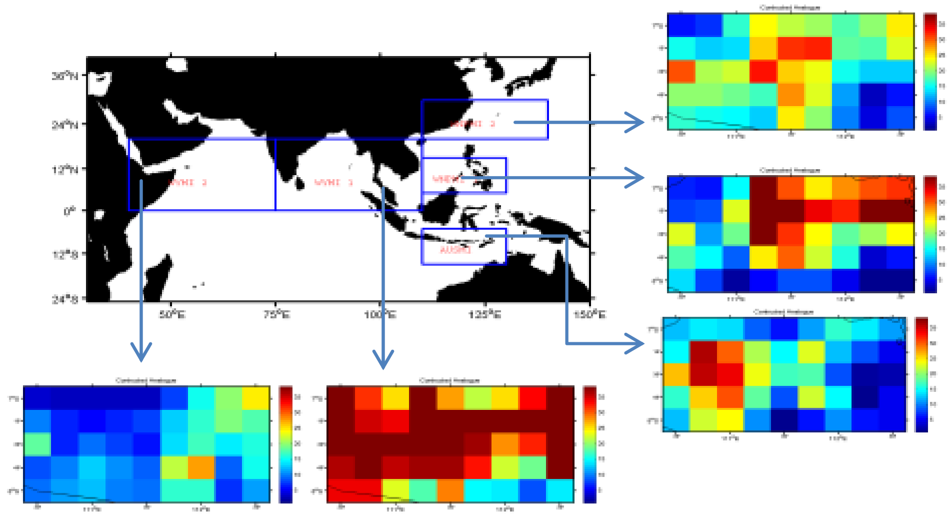


Figure 5. Example of CA output at a target time from 5 monsoon windows, using stream function predictor (ψ)

Based on Figure 5, a pattern in target from a particular GCM output (e.g. MIROC5) over particular windows (e.g. AUSMI) for a certain predictor (e.g. stream function) was searched for its similarities in baseline of predictors. The similar patterns, limited to 30, were collected and used to calculate coefficients of regression against a target of predictor. Meanwhile, the analogue of predictant (e.g. merged TRMM-APHRODITE) of the 30 similar patterns were collected and used to calculate a reconstructed analogue projection using the calculated coefficients of regression. Those processes were repeated for all predictors in all projections. Furthermore, those processes were also repeated for three GCM, two predictors, and five windows. As a result, the method provides 30 members of each day of projection (target).

4.2 Dynamical Downscaling Method and Data Required

There are several different approaches to dynamical downscaling, including from high-resolution global models, stretched-grid models and, the most common, limited area models (Katzfey 2014). Here, data from a regional climate model which was run at 50-km horizontal resolution globally with bias and variance corrected sea surface temperatures from six GCMs (see Katzfey 2016 for a more thorough description of the model and its setup) were used.

Downscaled simulations were completed for the period 1971–2100 for two forcing scenarios: RCP4.5 (representing a lower level of greenhouse gas emissions) and RCP8.5 (representing the highest emissions). Daily rainfall data was only extracted from the historical (1980–2005) and RCP4.5 scenario (2006–2040) from these runs for use in this assessment.

5 Evaluate climate model data

The assessments comprise of evaluation of the climate information from both the statistical and dynamical downscaled methods.

5.1 Baseline Dataset Pre-Analysis: Merged Gridded TRMM-APHRODITE

TRMM data was used as the baseline rainfall database because these data have a similar distribution pattern to station data (Figure 6). TRMM data is gridded, so the comparison between gridded datasets and station data was done by comparing the closest gridded data with station data.

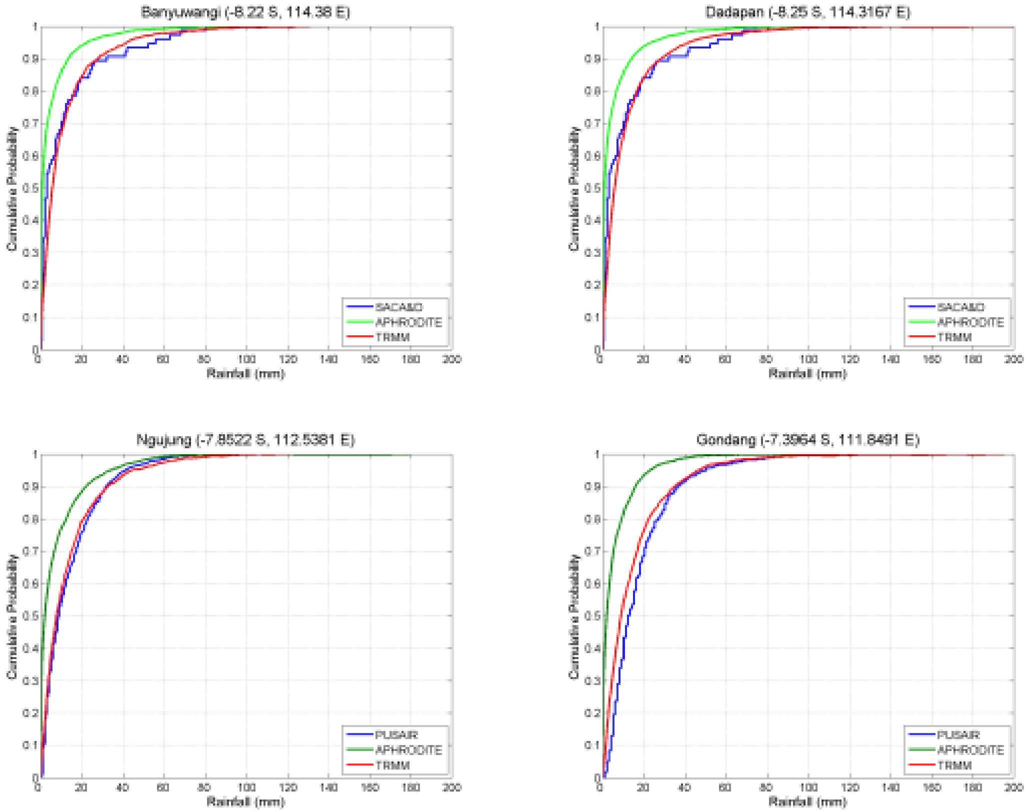


Figure 6. Sample validation results between gridded rainfall dataset, i.e. local rainfall data from SACA&D or PUSAIR (blue), APHRODITE (green), and TRMM (red), using cumulative distribution function (CDF) comparison. Samples were taken at Banyuwangi, Dadapan, Ngujung, and Gondang.

5.2 Baseline Climate Analysis

Baseline climate data were developed from the merged TRMM-APHRODITE dataset and six downscaled GCMs obtained from CSIRO as described above. Note that because the baseline climate data is the basis for the current climate in the statistical downscaling approach, analysis of it is not needed for the baseline period.

Figure 7 illustrates that the rainfall pattern over East Java is influenced by the monsoon. Observation (merged TRMM-APHRODITE) data and some models show one peak (in the Australian summer monsoon period) and one minimum (in the Asian summer monsoon period). While the dynamically downscaled results capture the annual cycle, the amplitude is somewhat reduced due to too much rain in the dry season and too little rain in the wet season. Although the RCPs had clearly defined the radiative forcing, its impact on rainfall projections was not linear, which is distinctly evident in the rainfall projection. There is no distinguishing pattern between each of the dynamical models since they were run using the same RCP. According to the previous work of Ministry of Public Works and Japan International Cooperation Agency (2015a), the RCP8.5 results only tend to produce a reverse (contrast) rainfall projection pattern against RCP2.6 output.

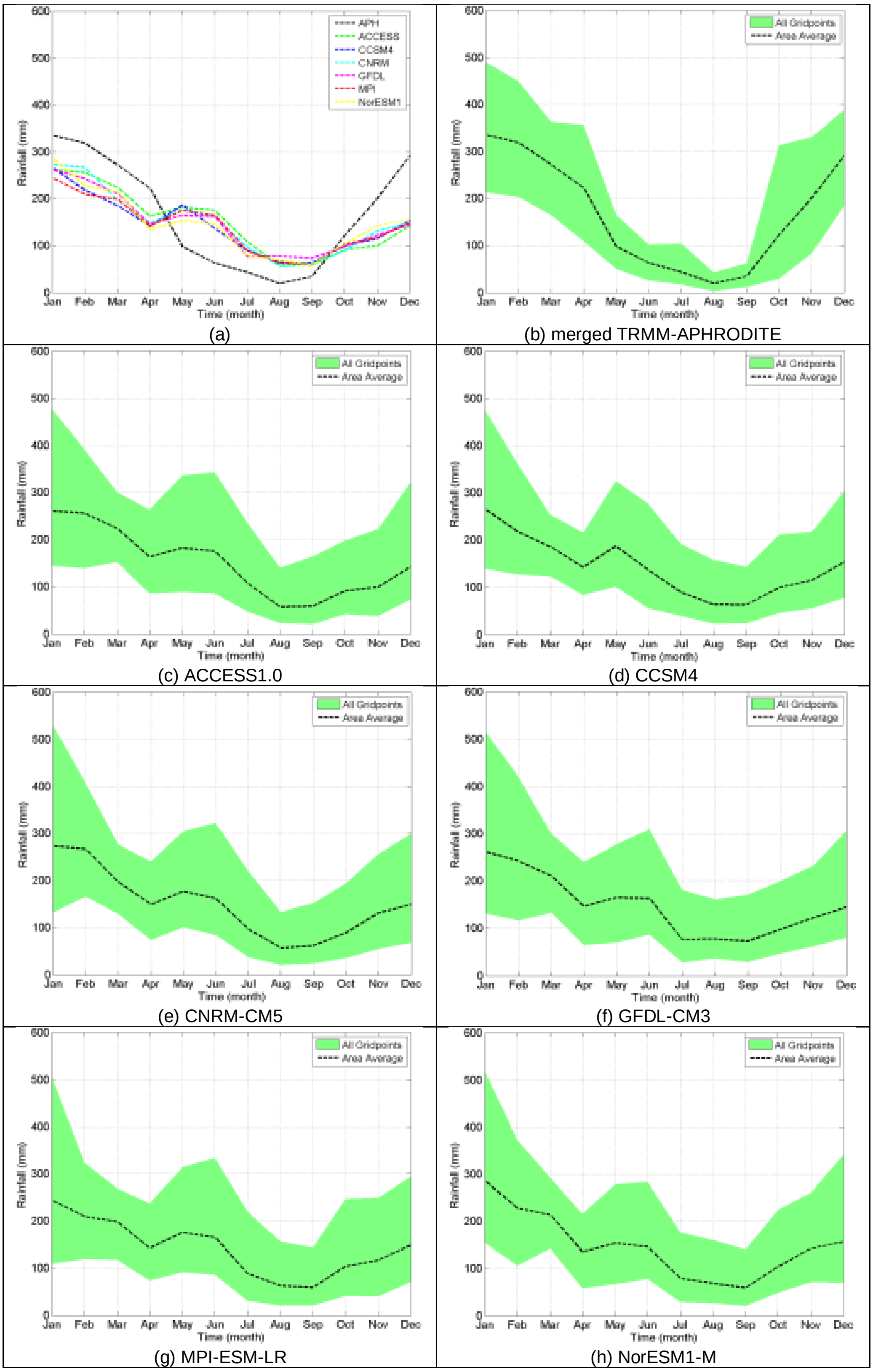
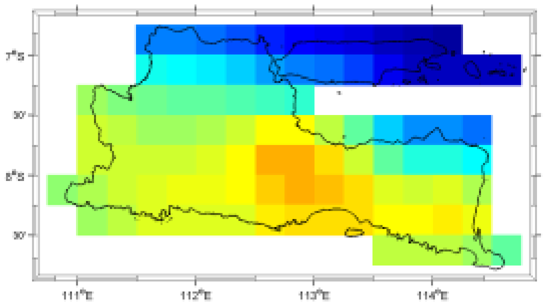
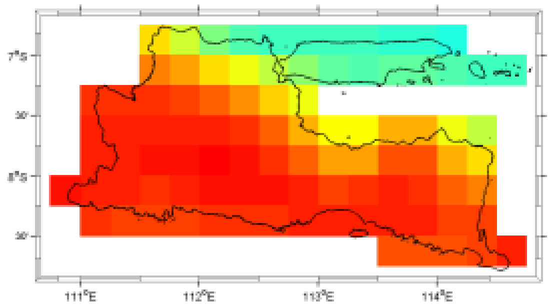


Figure 7. Long-term mean monthly rainfall (mm) over East Java region in baseline period. (a) APH: merge TRMM-APHRODITE data, (c) ACCESS1.0, (d) CCSM4, (e) CNRM-CM5, (f) GFDL-CM3, (g) MPI-ESM-LR, (h) NorESM1-M. Green shading indicates the range of rainfall each month. Dashed black line indicates area average of all grids.

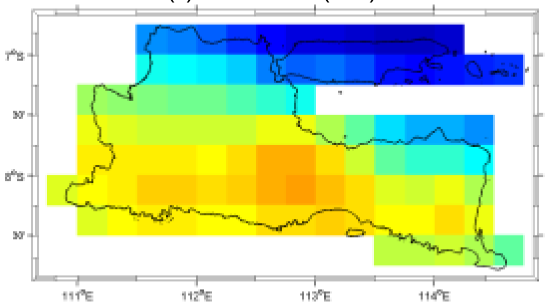
Figure 8 describes seasonal variation of rainfall spatial distribution over East Java, which is mainly driven by the monsoon. Based on baseline analysis, the rainfall peak should actually occur in January (December-January-February, DJF period), with the lowest rainfall period in August (June-July-August, JJA period). The dynamically downscaled results show that northern part of East Java is wetter than the southern part in both DJF and JJA. Whereas, observation shows that central part of East Java is wetter than region around it in, especially in DJF. The differences between dynamically downscaled results and observation indicated an effect of local topographic processes that are not able to be resolved by the GCMs resolution.



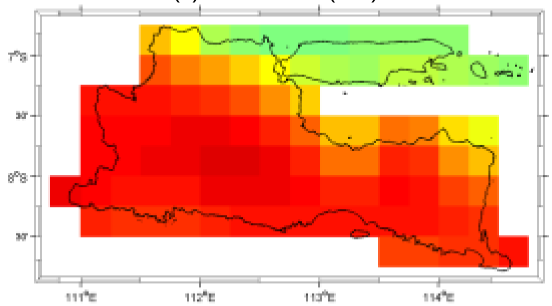
(a) ACCESS1.0 (DJF)



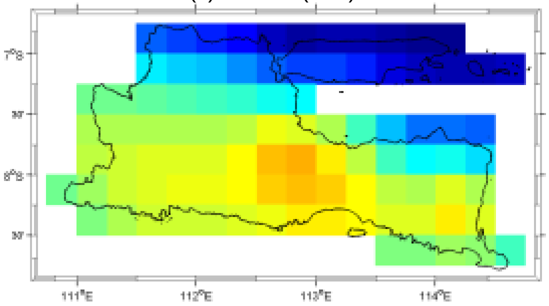
(h) ACCESS1.0 (JJA)



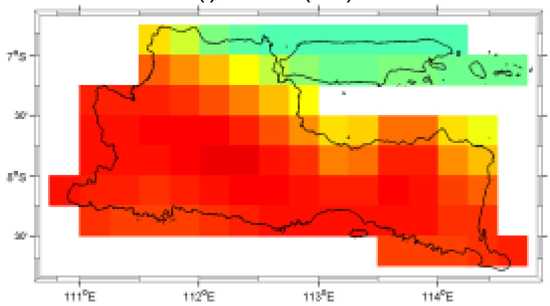
(b) CCSM4 (DJF)



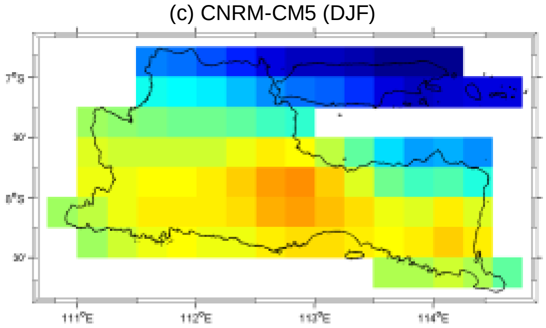
(i) CCSM4 (JJA)



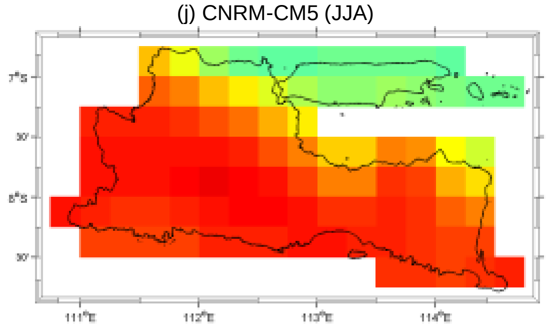
(c) CNRM-CM5 (DJF)



(j) CNRM-CM5 (JJA)



(d) GFDL-CM3 (DJF)



(k) GFDL-CM3 (JJA)

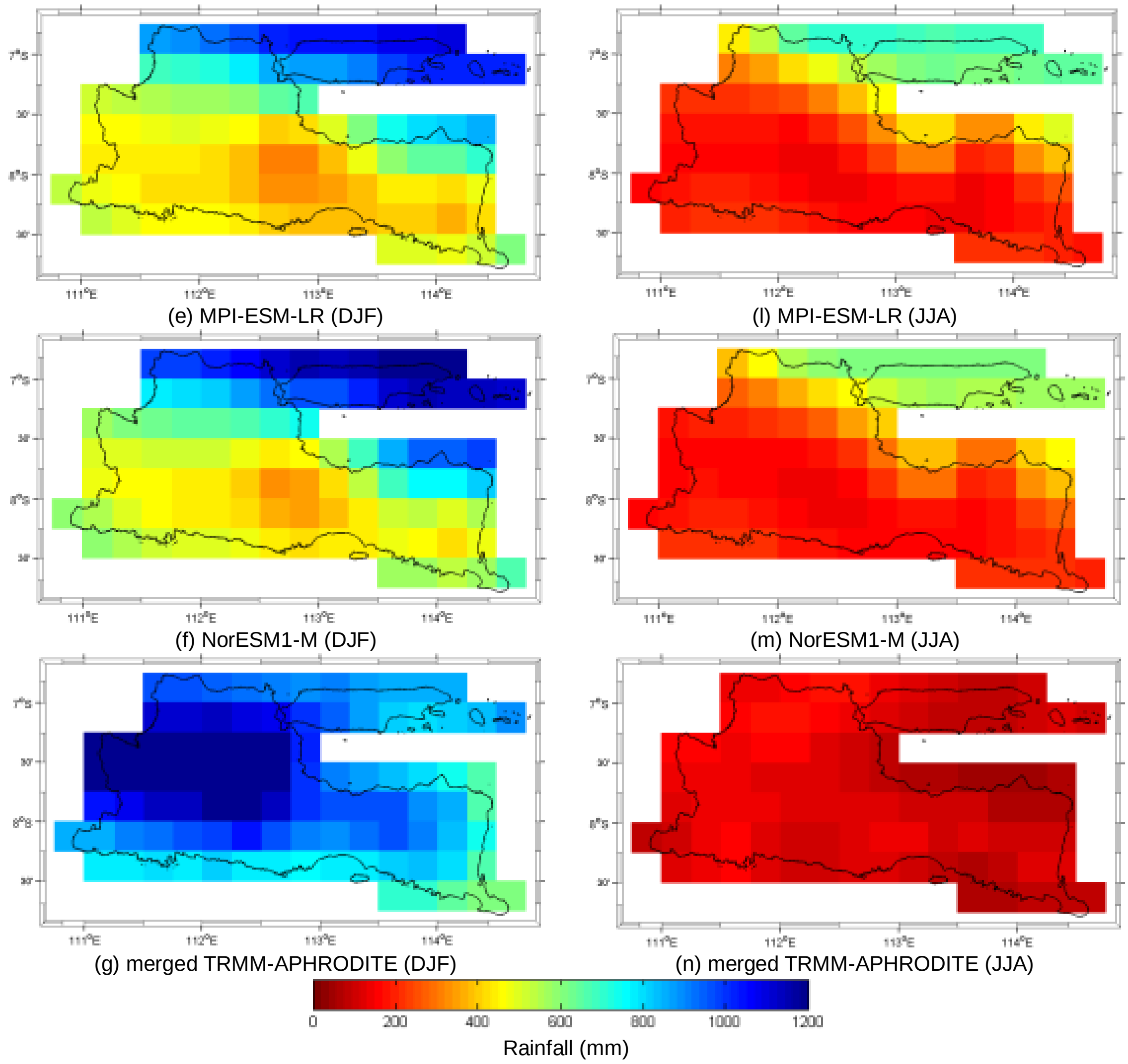


Figure 8. Spatial distribution of mean rainfall accumulation (mm) from (a & h) ACCESS1.0, (b & i) CCSM4, (c & j) CNRM-CM5, (d & k) GFDL-CM3, (e & l) MPI-ESM-LR, (f & m) NorESM1-M, and (g & n) merged TRMM-APHRODITE. Left (right) panel for DJF (JJA).

6 Select model

All the statistical and dynamical downscaled model data obtained in Step 4 were used in the analysis. They were statistically downscaled from three GCMs forced by the RCP4.5 scenario, and dynamically downscaled from six GCMs forced by the RCP4.5 and RCP8.5 scenarios. This allows the analyses to consider range of uncertainties related with the RCP scenarios, the GCMs and the downscaling techniques. The decision was based on an expert judgment provided in the previous work of the Ministry of Public Works and Japan International Cooperation Agency (2015a), data availability and the resource to conduct the analyses.

7 Construct projections

The computation of the drought index is described in Step 1 and in a separate training module (Fitriyanto et al., 2016).

8 Analyze projections

Two projections analyses were conducted in this case study. The first compares the future rainfall normal distribution against the current, while the second estimates projected changes in the climatological mean.

8.1 Projection for rainfall normal distribution

Figure 9 and Figure 10 each illustrate the normal distribution of rainfall data averaged over East Java region for the baseline period (1981–2010) and projection period (2011–2040). The statistical downscaling output (Figure 9) shows that projected mean is very similar to those of the baseline. However, there is an increased probability on rainfall near the baseline mean and a reduced probability of rainfall amounts greater than about 300 mm. Furthermore, standard deviation in projection is lower than in baseline, suggesting a less variability in rainfall in the future.

The normal distributions from the dynamical downscaling outputs show varying results (Figure 10). Some models (ACCESS1.0, CCSM4, and CNRM-CM5) show that the projected mean is lower than the baseline. On the other hand, GFDL-CM3 shows that projected mean is higher than that of the baseline, and MPI-ESM-LR and NorESM1-M show that the projected mean is similar to the baseline. In addition, all models show that projected standard deviation is similar to the baseline.

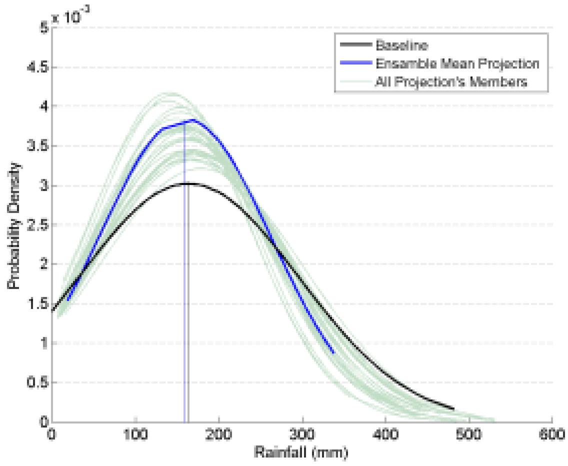


Figure 9. Normal distribution of area-average over East Java of monthly rainfall of merged TRMM-APHRODITE. Black line for baseline (1981–2010). Blue lines for projection (2011–2040), using statistical downscaling outputs, which are all projections members (light blue) and ensemble mean (dark blue). Vertical lines denote mean values.

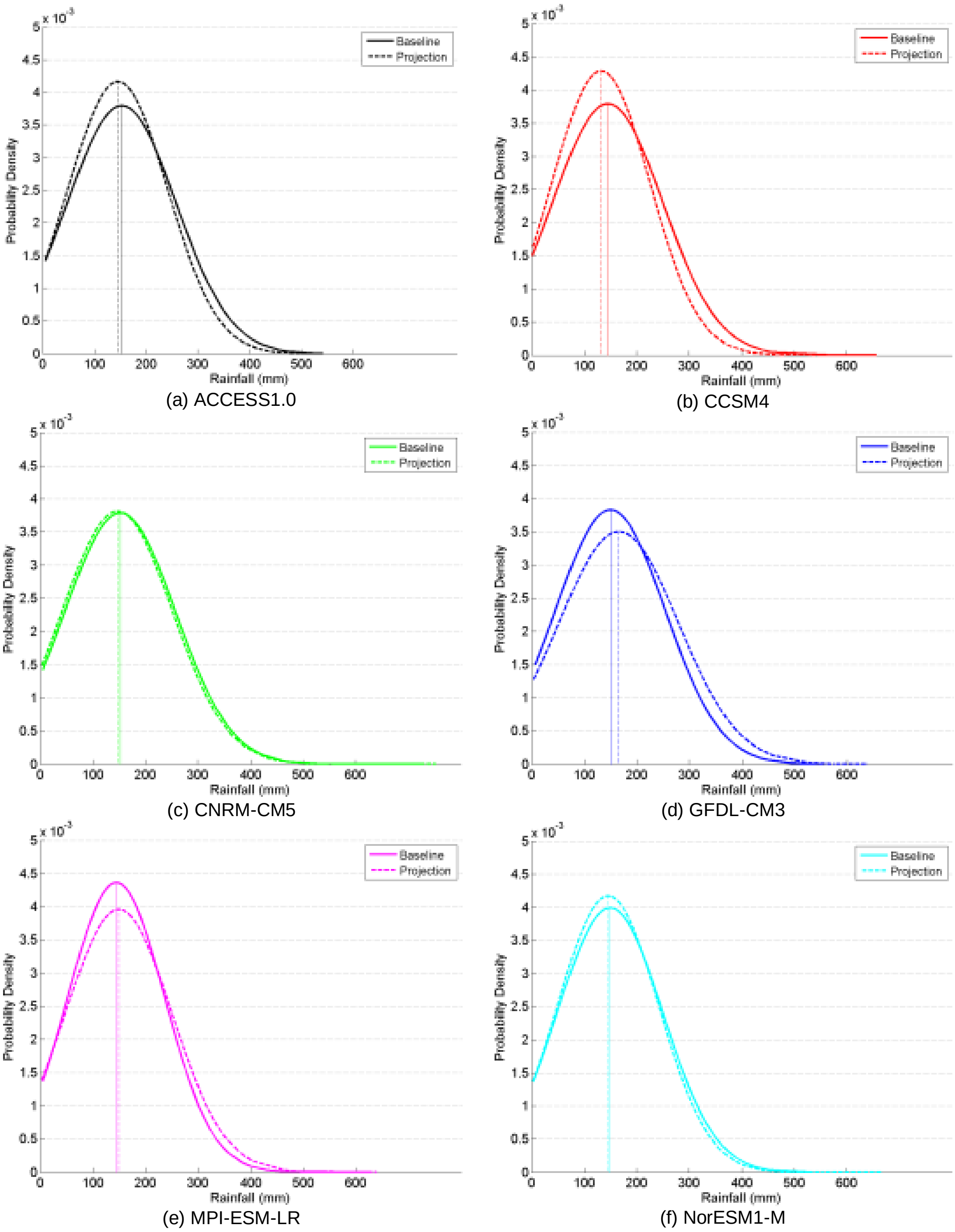


Figure 10. Normal distribution of area-average over East Java of monthly rainfall from dynamical models namely a) ACCESS1.0, b) CCSM4, c) CNRM-CM5, d) GFDL-CM3, e) MPI-ESM-LR, and f) NorESM1-M. Solid lines denote baseline (1981–2010) and dashed line denote projection (2011–2040). Vertical lines denote mean values.

8.2 Projected changes in climatological mean

Figure 11 indicates that the projected seasonal pattern (2011–2040) is similar with that of the baseline (1981–2040). However, the projected rainfall in January and February are lower than those in the baseline. The spread of all models ensemble (pink shaded) is relatively small, suggesting small uncertainty in rainfall projections. The dynamical models outputs also suggest similar results (Figure 12).

None of the three models shows increased rainfall (Figure 13). Figure 13 also suggests that the dynamical models' outputs show larger change in monthly rainfall amplitude than statistical models' outputs do.

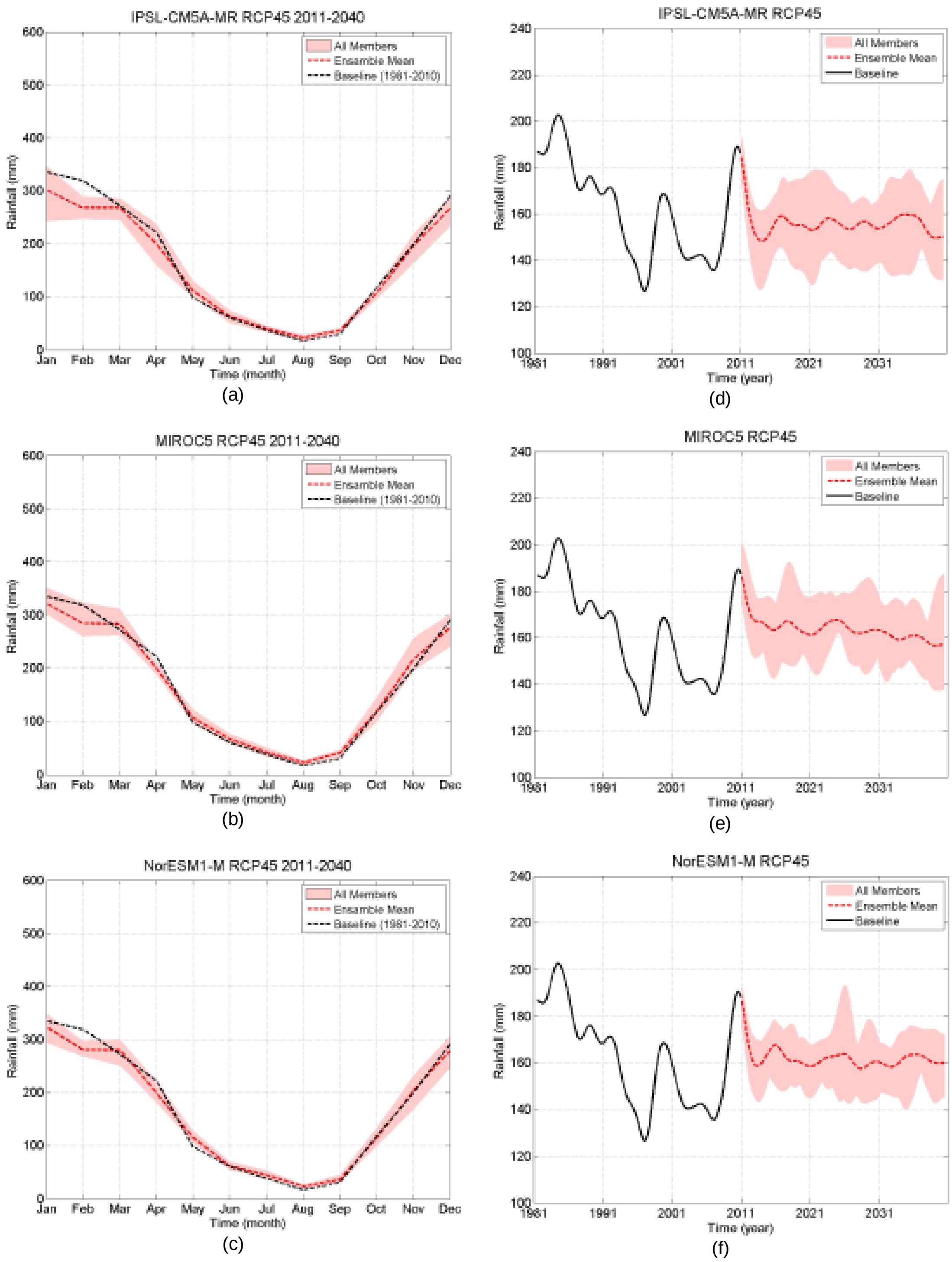


Figure 11. (Left panel) 30-years climatological mean (composite) of downscaled rainfall projection (2011–2040), averaged over East Java region for (a) IPSL-CM5A-MR, (b) MIROC5, and (c) NorESM1-M-M using RCP4.5 scenario. Pink shade denotes all ensemble members spread (plume plot). Red line denotes the ensemble mean. Black line shows baseline climate rainfall (1981–2010). (Right panel) Smoothed monthly mean time series of downscaled rainfall projection from (d) IPSL-CM5A-MR, (e) MIROC5, and (f) NorESM1-M-M using RCP4.5 scenario. Pink shade denotes

all ensemble members spread (plume plot). Red line denotes the ensemble mean. Black line shows baseline climate rainfall.

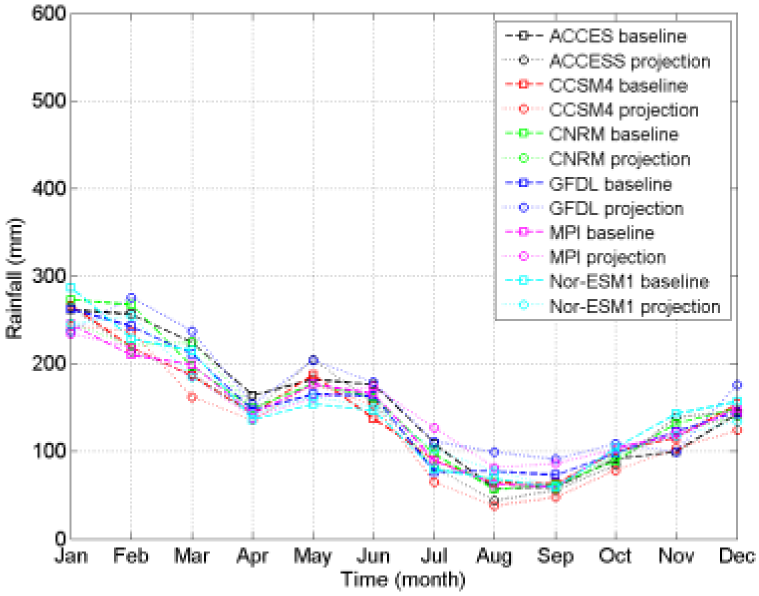


Figure 12. The 30-year climatological mean (composite) of rainfall projection (2011–2040) and baseline (1981–2010), averaged over East Java region from dynamical models using RCP4.5 scenario. Further explanations see the figure.

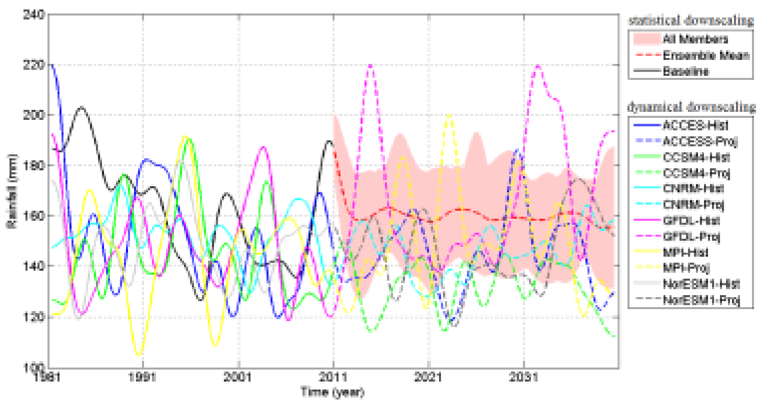


Figure 13. Smoothed monthly mean time series of downscaled rainfall projection from statistical and dynamical downscaling using RCP4.5 scenario. Further explanations of colors see the figure.

8.3 Confidence and uncertainty in projections

For the statistical downscaling approach, a suitable large number (i.e. 30; see Step 4) of GCM-based datasets were needed to provide a good confidence. Moreover, the use of observational data for representing the historical period gives a more realistic starting point. However, the projections shown in Figure 13 show very little interannual variability and variation over time, which seem to be less realistic. These reduce confidence in the predictions rising needs of further investigation on some physical phenomena or even datasets used to explain about why this could occur, for example the quality problem of the use of TRMM data merged with APHRODITE data (see Step 2).

The dynamical downscaling results indicate biases for the current climate. Although the simulations capture the observed annual cycle, they show smaller amplitude: the downscaling results showed less simulated rain in the wet season and too much simulated rain in the dry season in comparison to the observation. In addition, the spatial pattern of the modelled rainfall is rather poor. Contrary to the explicit trend of temperature increase, simulation and projection of rainfall did not show perceivable pattern since model resolution was too coarse and thus could not represent the local rainfall distribution well.

In order to gain greater understanding of the range of possible futures and to place the downscaled results here in context, it is highly recommended for the climate experts in Indonesia that the changes projected from the full range of GCMs be evaluated as it needs more extensive efforts.

9 Correct possible biases

As noted in Step 2, a bias correction technique was applied to the APHRODITE dataset in order to make it more similar to the TRMM and station data. This bias correction process was required for the analysis of the statistically downscaled model outputs.

In the analysis of the dynamically downscaled climate simulations for the current period, some significant biases were also noted, both in the seasonal distribution, but also spatially. While outside the scope of this project, bias correction of the dynamically downscale simulations could have been done. However, since the main emphasis of this study is the changes in droughts this step was not done here (see, for example, Dai (2011), which shows that studying projected changes in drought could be conducted by comparing model's simulation for the future against the present without the need to conduct bias correction).

10 Assess drought hazard and communicate results

Drought hazard assessment completed here is based upon changes in the frequencies of the Standardized Precipitation Index (SPI) of 3- and 6-monthscales and Dry Spell (number of no-rain days during wet seasons). The results are communicated through maps.

10.1 Drought Hazard Index from the Statistical Downscaling Results

Merged TRMM-APRODHITE rainfall dataset was used as input to calculate the Drought Hazard Index (DHI) through its components of Dry Spell, SPI-3, and SPI-6. Figure 14 shows the map of DHI values in the East Java Province for baseline period; plotted in 0.25° grids.

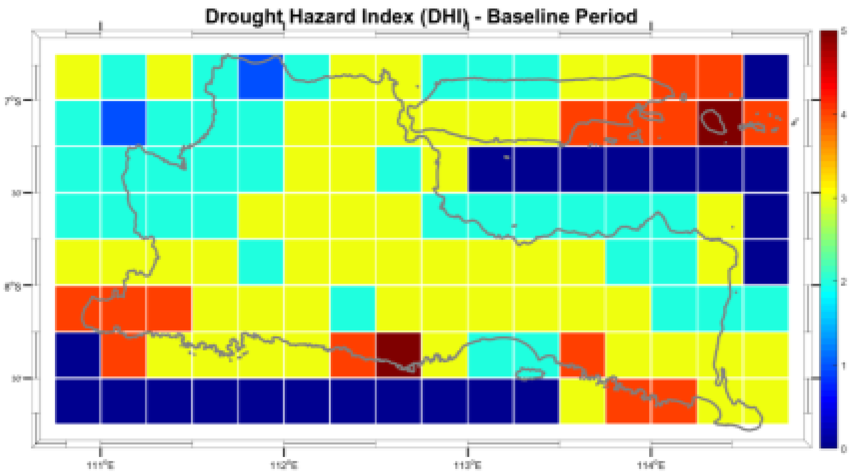


Figure 14. Drought Hazard Index (DHI) in baseline period based on results of statistical downscaling

The DHI map indicates that drought hazard is high over the southern parts of East Java Province compared to over the northern areas. This result is in line with the SPI-3 calculation of less than –1.5

(severely dry) and historical drought records as described in Table 3. However, we suggest to further verify this result with observation data for more detailed analysis.

Due to intangibility character of drought hazard (in comparison to other hazards such as flood, landslide, coastal inundation), the projected condition of DHI is then calculated with the term of DHI increases in the projected period from the baseline rather than of projected DHI values. The DHI increase values are calculated from the downscaling results of rainfall. For example, by the statistical downscaling, 30 datasets were generated so-called as members to produce 30 projected DHI values in each particular location. We would then find numbers of the 30 projected DHI values which increase at least 5 units from the baseline DHI value. If the numbers of increased projected DHI values are more than the threshold value (e.g. 50% of 30 members), then we assume that the projected DHI value is one unit increase of the baseline ones. Each of the projected DHI values was compared to the baseline ones to construct a probability map showing increased DHI (see Figure 15).

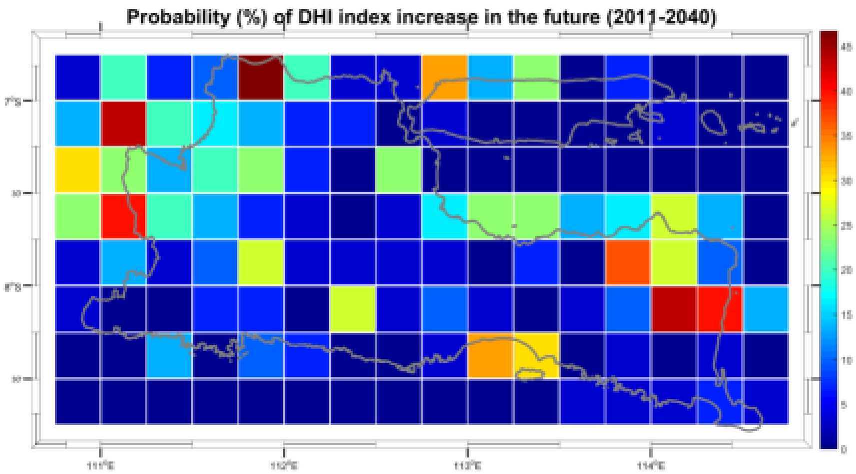


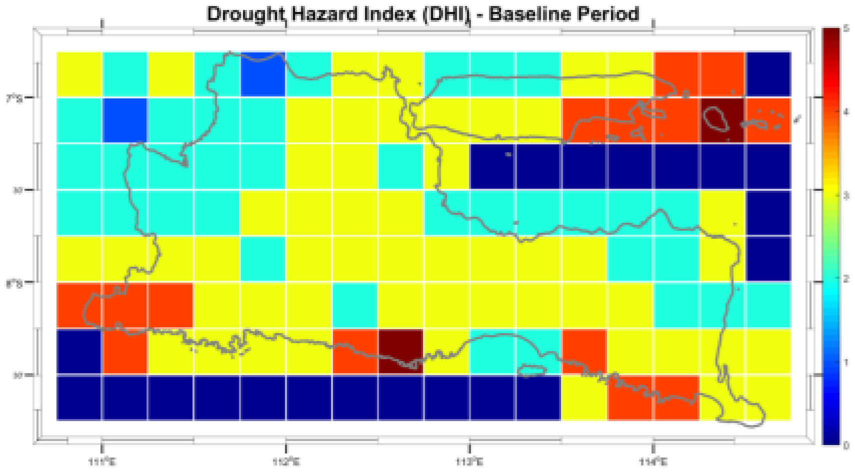
Figure 15. Probability (%) of DHI Increase in Future Period (2011 – 2040) based on results of Statistical Downscaling

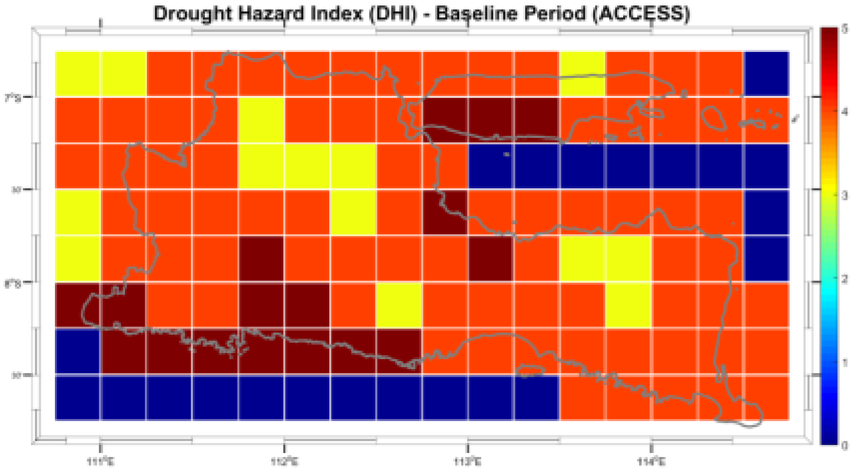
Probability of increased projected DHI map shows that the North West and East parts of the East Java Province have relatively high probabilities of DHI increasing in the projection period.

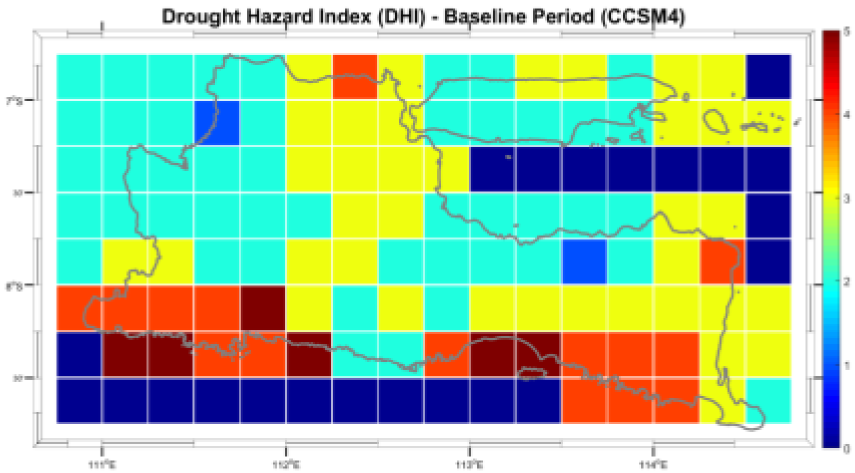
10.2 Drought Hazard Index from the Dynamical Downscaling Results

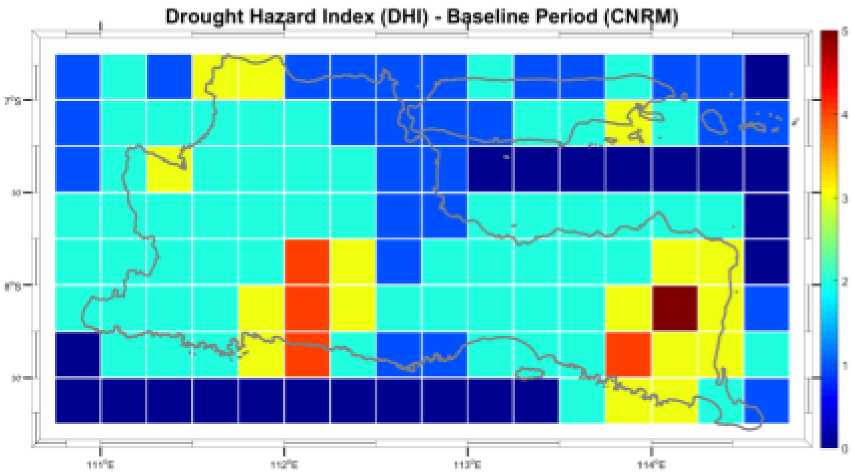
In this case, the DHI values both for the baseline period and future periods we calculated from rainfall provided by the six downscaled GCMs (i.e. ACCESS1.0, CCSM4, CNRM-CM5, GFDL-CM3, MPI-ESM-LR, and NorESM1-M). A series of DHI value maps are presented in Figure 16 and Figure 17.

Baseline Period









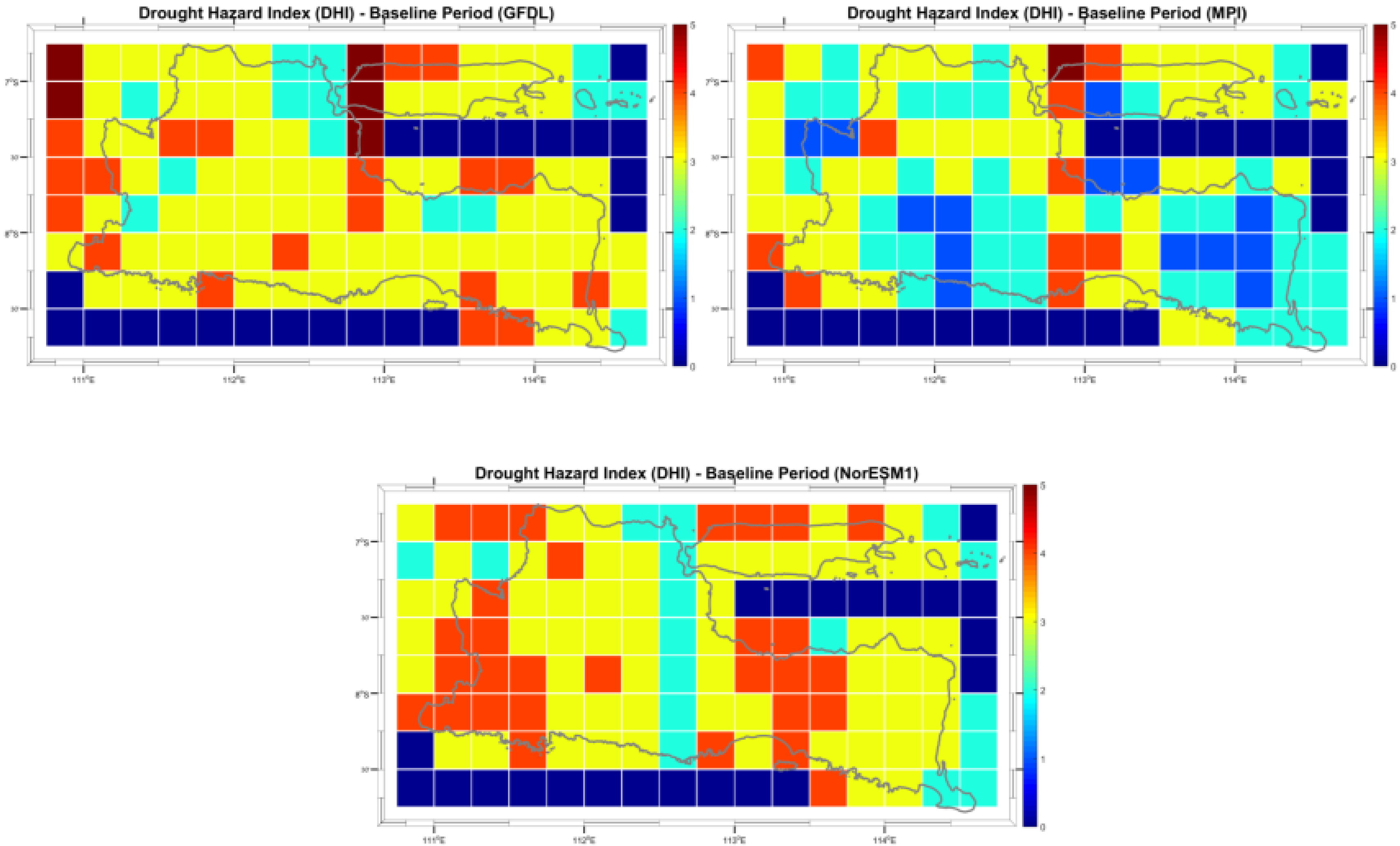
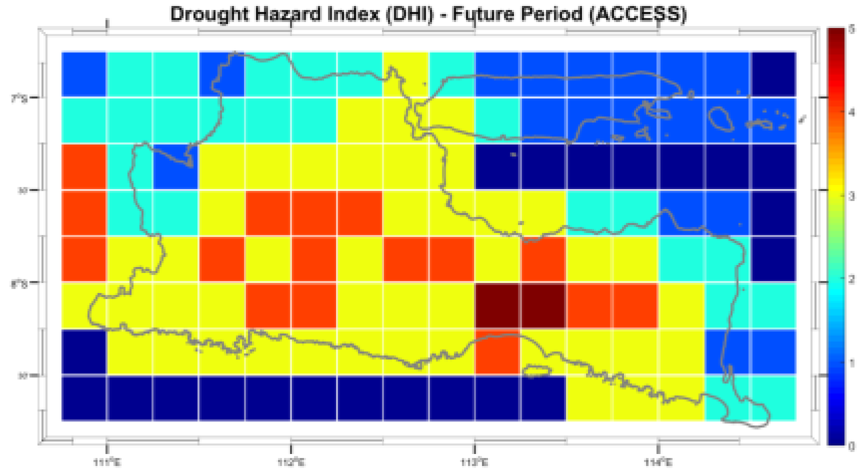
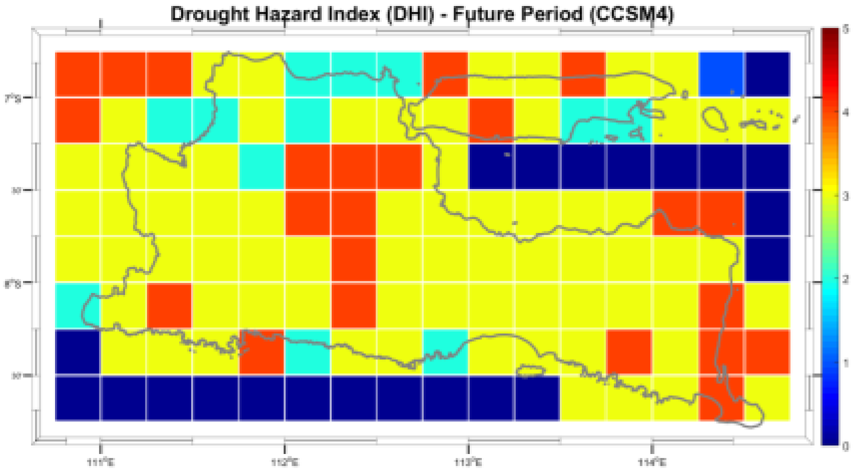
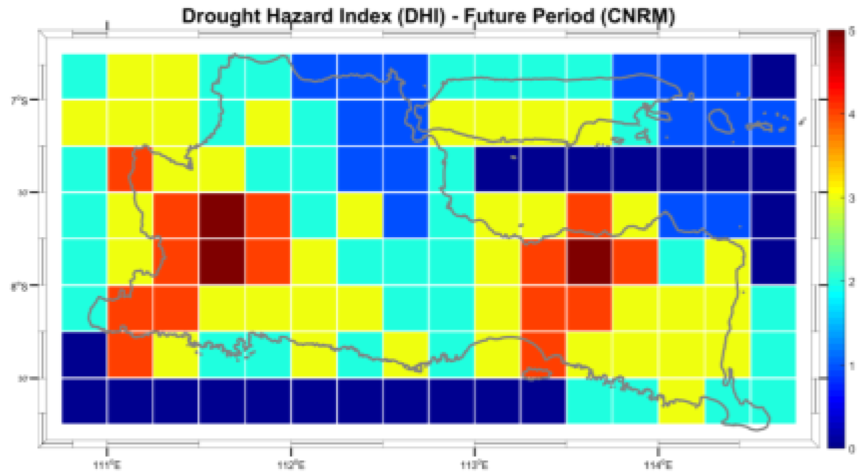


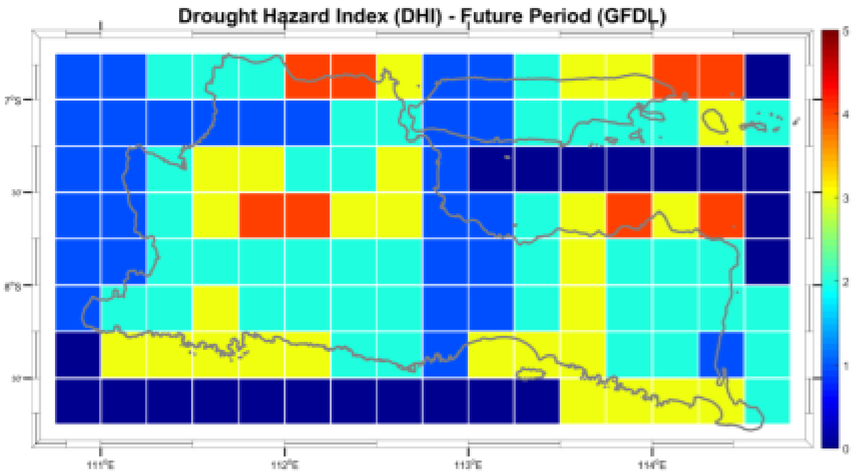
Figure 16. Comparison Drought Hazard Index (DHI) for Baseline Period among Baseline Data with Global Climate Models (Dynamical Downscaling) Results

Projection Period









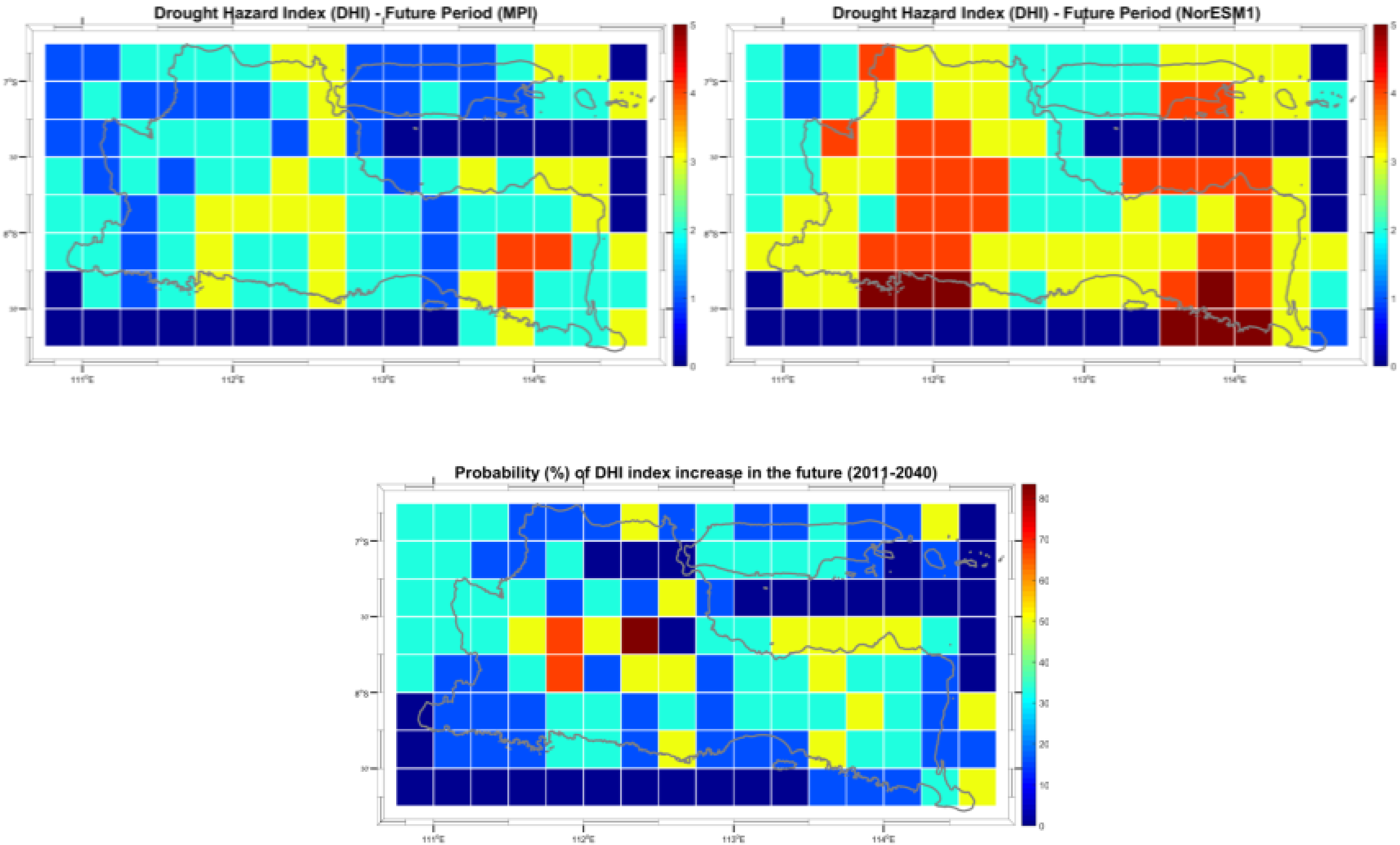


Figure 17. DHI and Probability (%) of DHI Increase in Future Period (2011 – 2040) Based on Global Climate Models (Dynamical Downscaling) Results

CONCLUSIONS AND RECOMMENDATIONS

This case study is designed to strengthen technical capacity of the in-country TA project team, through learning by doing, to access and use climate science data for projection analysis and climate risks assessment as per the guideline developed in TA-8359 and available on the RCCAP portal (www.rccap.org). In particular, this case study demonstrates how climate projection information can be developed, as part of a drought hazard assessment for supporting climate adaptation in the spatial planning sector in the East Java Province, Indonesia.

The results suggest that monthly rainfall distribution over the Province in the future (2011–2040) is likely to be similar to that of the baseline period (1981–2010). However, there will be less probability of receiving rainfall greater than 300 mm (Figure 9 and Figure 10). Although the use of statistical and dynamic downscaling methods each indicates a slightly different rainfall projection, the overall results point to a similar trend – that the future seasonal rainfall pattern will be similar to that of the present and that no single model suggests a possible increase in rainfall in the future (Figures 11–13). The potential increase of the Drought Hazard Index (DHI) in the future is noteworthy, with some locations showing a probability of increased drought of up to 45% (Figure 15).

The fact that the downscaling outputs by different techniques or methods produce slightly different projection results is understandable due to dissimilarities in modelling processes (e.g. Kirono et al., 2016). In this context, one does not need to treat the statistical downscaling method as superior to the dynamical downscaling method, or vice versa. Instead, one can consider both results to represent plausible future projections. The implication is mainly in the different uses or implementation of the methods. Dynamical downscaling needs huge computational efforts (several months continuous computation with a high-performance computer); however, it will provide comprehensive results in the context of all Indonesia country-wide. Use of statistical downscaling requires less effort as it depends only on some provided GCM data and station/observation data at/nearby the location of study. In the context of adaptation planning (both in development and spatial planning), use of dynamical downscaling is urgently required in national and regional assessments, while assessment in a single location needs only statistical downscaling. However, implementation of both methods requires model verification/validation by data in the baseline period, where more data are needed by the dynamical downscaling method than the statistical one.

The results are presented in a form of graphs (e.g. Figure 12) and maps (e.g. Figure 17). Similar maps can then be produced for other climate related hazards (e.g. landslide and flood, see Figure 2) from the same climate information to describe the overall possible ‘hazard’ in the assessment location. After that, the hazard measures can be combined with the specific hazard-related ‘vulnerability’ measures to estimate specific hazard-related ‘risk’ measures. Then, adaptation options can be formulated and recommended as appropriate to each type of hazard-vulnerability-risk. All assessments of hazards should be informed by sufficient ranges of both baseline and projected climate (i.e. at least 30 years’ time span of data each – in accordance to time period of climate definition by the World Meteorological Organization – as presented in this case study).

The graphs and the maps can also be used in any climate change related communication and activity. However, they may require some modification tailored to the need of different users or audience.

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APPENDIX

Types and Sources of Data

TRMM: Tropical Rainfall Measuring Mission
(Huffman et al., 2007)

http://mirador.gsfc.nasa.gov/cgi-bin/mirador/granlist.pl?page=1&location=%28-90,-180%29,%2890,180%29&dataSet=TRMM_3B42_daily&version=007&allversion=007&startTime=1997-12-31T00:00:01Z&endTime=1997-12-31T23:59:59Z&keyword=TRMM_3B42_daily&longname=Daily%20TRMM%20and%20Others%20Rainfall%20Estimate%20%283B42%20V7%20derived%29&CGISESSID=2f6fa2c6d4ea5e99df0ba8114d1f0461&prodpg=http://disc.gsfc.nasa.gov/datacollection/TRMM_3B42_daily_V7.html

APHRODITE: Asian Precipitation—Highly-Resolved Observational Data Integration towards Evaluation
(Yatagai et.al., 2009; Yatagai et.al., 2012)

http://www.chikyu.ac.jp/precip/index.html

Observation Data
(Ngujung Station)

Source: PUSAIR (Research and Development Center of Water Resources– Ministry of Public Work and Settlement, Republic of Indonesia).

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