Evaluation of Regional Climate Model Simulated Rainfall over Indonesia and its
Application for Downscaling Future Climate Projections

THESIS

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Abstract

The need for good quality information on climate and its future changes have become increasingly important for Indonesian society. Of particular interest are analysis and predictions of rainfall at pertinent spatial scales. An option is the use of regional climate models as a physics-based downscaling tool to retrieve higher spatial resolution information from coarser present and future climate datasets. In order to verify that simulations provide added values that result in an appropriate representation of the state of climate at finer spatial resolutions, the adoption of regional climate models requires prior optimization. The performance of a regional climate model (WRF, Weather Research and Forecasting Model) in simulating precipitation over Indonesia is examined by a series of sensitivity experiments using different parameterized convective physics. Among tested schemes, the best performance is provided by the Betts-Miller-Janjic parameterization. Regional simulation results present some added value in simulating rainfall-related climate indices but show low skill in recreating the annual rainfall pattern. A series of regional climate simulations using the Betts-Miller-Janjic convective scheme forced by a future climate projection dataset show changes in rainfall aligned with previous studies.

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Chapter 1: Introduction

The need for climate projections has become an important aspect of primary livelihood activities, particularly in emerging economies such as Indonesia. Complicating prediction efforts is the fact that the country's location and complex geographical setting result in a large range of very distinct climate conditions. Indonesia is located in the tropics between the continents of Asia and Australia, in the area commonly known as the maritime continent region, being comprised by a densely populated chain of islands of various sizes. Among its unique features is the large influence exerted by islands on local atmospheric dynamics (Neale and Slingo, 2003).

As precipitation interacts with many living sectors of the population and, given the relatively small temperature range compared to the higher latitudes, much of the effort on weather and climate prediction and analysis in Indonesia is focused on precipitation and its derivative products. The variability of rainfall is an issue, as it controls the livelihood of a large section of the population for whom farming and fisheries are the primary economic activities. Attempts to understand the various mechanisms that contribute to the spatial and temporal variability of rainfall in the area still face many challenges. Strachan (2007) has documented the complexity of the maritime continent dynamics and proposed future modeling research guidelines to address the rainfall predictability issues. A study that analyzed a long-term period (from

1950 to 1998) of rainfall with numerous surface observational data from Indonesia found that the wet season rainfall has a systematic predictability problem, with only a small portion of the country's area exhibiting high loadings in the low-order components of their principal components analysis (PCA), implying that most areas show small coherence in interannual rainfall variation. The study also found that some rainfall patterns in neighboring stations have inconsistencies, hindering predictability, especially during the peak of the monsoonal rainfall cycle in December-January-February (Haylock and McBride, 2001).

Another issue is the complex spatial variability of rainfall. Indonesia is part of the Pacific volcanic "Ring of Fire" with portions of the country located at the intersection of active tectonic plates and characterized by a narrow band of islands containing mountain chains along their main axes. In these areas, orographic effects have an important impact on rainfall by influencing cloud merging process and the intensity of convection (Saito *et al.*, 2001). The general rainfall pattern of Indonesia has been categorized by Aldrian and Susanto (2003) into three different main types. One, covering the central and south portions of the nation, is generally influenced by the Australian monsoon. Another is found over western and northern areas, where precipitation exhibits two peaks per year. Both of these patterns are heavily influenced by the Asian monsoon and the Intertropical Convergence Zone (ITCZ). The last pattern occurs in Moluccas region, along with the eastern portion of the Indonesian Through Flow. Still, several areas within the country are subject to local rainfall variability that does not fit these categories. There are more than 200 climate zones in Indonesia where precipitation varies in

accordance with three main dominant patterns, but this is not the case in more than 70 other zones.

Many stakeholders require climate information continuously distributed in time and space. Due to the large heterogeneity in the behavior of precipitation over Indonesia, these societal demands cannot be met, for example, by the practice of interpolating point surface observations from available meteorological stations. Numerical models, with continuous spatial and temporal coverage, could help with this problem. Most modeling institutions offer products that assimilate observations into the modeled output and data from several short- and long-term projections, covering various scenarios, are freely available. In terms of predicting future climate, models are currently the best available tools (Lynch, 2008).

However, several past efforts have pointed out that, over Indonesia, numerical climate models do not represent well some dynamical features important to precipitation such as monsoon and diurnal cycles, land and sea breezes and convection (Aldrian, 2003; Aldrian *et al.*, 2004; Collier and Bowman, 2004; Qian, 2008; Love *et al.*, 2011.). Models have struggled to reproduce rainfall statistics such as wet-dry periods as well as extreme events (Kitoh and Arakawa, 1999; Lau and Nath, 2000; Gianotti *et al.*, 2012; Gianotti and Eltahir, 2014). There are indications that GCMs' poor representation of atmospheric dynamics over the maritime continent, including their inability to reproduce variability at the seasonal timescale, is related to the absence in these models of the small-scale convection processes that commonly occur in the area (Slingo *et al.*, 2003). Simulation of processes at the scale of convection would require spatial resolutions in the order of 1-25

km (the range of cumulus to thunderstorm convection), significantly higher than that of average GCMs, with resolution ranging from ~100 to 250 km. Given the commonly available computational resources at both operational and research centers, GCM simulations at the resolutions required by the problem at hand are not viable.

An alternative is the adoption of limited area, or regional climate models (RCMs). In terms of simulating past and present precipitation, several efforts have shown that regional simulation results provided added value by generating output that better match observations, and also by offering a better representation of the small-scale dynamics that low-resolution models fail to capture (Christensen *et al.*, 2001; Lim *et al.*, 2011; Cavicchia and von Storch, 2012; Di Luca *et al.*, 2012; Berg *et al.*, 2013; Im *et al.*, 2014). Efforts have been made to introduce procedures that could enhance the performance and accuracy of regional climate simulations. These include the modification of parameterized physics options, improvement of forcing datasets by data assimilation process, and coupling with other types of regional models that provide feedback mechanisms (Gianotti and Eltahir, 2014; Wei *et al.*, 2014; Fonseca *et al.*, 2015). Potential problems of using RCMs for precipitation predictions include issues with model internal variability, non-optimal boundary conditions - such as land-surface and sea surface temperature- and, nesting feedback, all of which have the potential to affect the accumulated precipitation in the long term (Bukovsky and Karoly, 2009). Attention should also be paid to the selection of the appropriate convective physics, as this is the most sensitive subroutine in the model calculation of simulated precipitation (Kim and Wang, 2011; Zeyaeyan *et al.*, 2017)

RCMs have been used to investigate the maritime continent region climate. Some worth noting are briefly described below and discussed in more detail in next chapter. Hayashi *et al.* (2008) conducted statistical analysis of results from multiple RCMs. Regional simulations have been used to analyze the diurnal cycle of convection, a very important control for daily rainfall in the area (Hara *et al.*, 2009). Other RCM experiments in Southeast Asia have focused on measuring the strength of the simulated water cycle (Ulate *et al.*, 2014) and analyzing hydro-climatic change (Tue, 2012). The wind field results from RCMs have been utilized as input for an air quality model that simulates biomass burning and smoke transport from forest fires during El-Nino (Huang *et al.*, 2013; Wang *et al.*, 2013).

Recently, there has been an increase in the use of climate information as one of the main inputs for various sectoral impact assessments as well as adaptation strategies. These efforts make use of expert recommendation in order to reduce the future impact of climate change on society. Many of them deal with the impacts of extreme events, which according to a growing body of evidence will tend to increase in certain regions as a result of anthropogenic global warming (IPCC, 2015). According to Yusuf and Fransisco (2009), Southeast Asia has the most critical needs for policies in response to climate change risks. As part of the Southeast Asian community, Indonesia is not safe from these threats. The government of Indonesia has to strategically address the possible impacts and compose response actions by forming a resilient society (Case *et al.*, 2007). Central to the success of such initiative is good quality historical climate analysis and skillful projections of future climate trends.

Research on the impact of climate change in Indonesia has focused on the analysis of observed extremes. Siswanto *et al.* (2015a) describe the change in temperature and rainfall extremes for the city of Jakarta in the last 130 years and pointed to the Jakarta flood in 2014 as corroborating evidence for the increase in the intensity of extremes (Siswanto *et al.*, 2015b). The 2015 Jakarta flood was also investigated in the context of climate change (Siswanto *et al.*, 2017). The variability and trend of indices relevant for crop production were examined by Marjuki *et al.* (2016). Supari *et al.* (2017a) performed a thorough analysis of observed rainfall and temperature indices trends for all Indonesia. Over the maritime continent area, extreme low precipitation associated with drought cases, and excessive rainfall, associated with floods, are often attributed to the ongoing phase of the multiannual El-Nino Southern Oscillation (ENSO) in the Pacific Ocean (Barsugli and Sardeshmukh, 2002; Wang *et al.*, 2003; Juneng and Tangang, 2005).

Rummukainen (2016) has highlighted and summarized the common practice for the utilization of regional climate models as tools that provide added value to the limited area or regional climate information. Also discussed in the study is the feasibility of downscaling future projection data using regional climate models. An example of this type of effort is described in Lee and Hong (2014), who used RCMs for analyzing climate extremes over the Korean peninsula and found some added values, supporting the adoption of RCMs in this context. Several earlier studies have utilized RCMs to provide a more detailed description of future climatic changes, with most of them including precipitation as a part of their analysis (Andersson *et al.*, 2006; Salathé *et al.*, 2008;

Salathé *et al.*, 2010). An example is the comprehensive future vulnerability assessment developed by Giorgi and Lionello (2008) for the Mediterranean region, a collaborative effort with participation of different institutions from several nations. For the maritime continent area, a study by Chotamonsak *et al.* (2011) used a regional model to generate downscaled temperature and precipitation predictions using future projections dataset from the Coupled Model Intercomparison Project Phase 3 (CMIP3). In a collaborative effort within the Coordinated Regional Downscaling Experiment (CORDEX) framework, experiments with the RegCM4 regional climate model were used to test the sensitivity of simulated temperature and rainfall to different parameterization schemes (Juneng *et al.* 2016; Ngo-Duc *et al.* 2017; Cruz *et al.* 2017).

Here I aim to generate references for best practices for RCM-based climate projections in the maritime continent region, with a focus on the clearly identified need for practical future climate change information in Indonesia. A series of experiments, in which low-resolution global datasets are nested and downscaled into a higher spatial resolution of 20 km, is performed. In general, this study can be separated into two parts. In the first part, a series of RCM-based historical experiments are conducted under different ENSO states in order to evaluate how different convective parameterization schemes impact the model's skill in reproducing several precipitation indices. In the second part, the previously identified most skillful parameterization is adopted by RCM simulations aimed at investigating future changes in rainfall over Indonesia.

Chapter 2: Literature Review

2.1 Climate of Indonesia

2.1.1 Geography

Indonesia is an archipelagic state comprised of at least 13,000 islands located in Southeast Asia. It is intersected by the equator with the majority of the land area located in the Southern Hemisphere. The country is surrounded by two continents, Asia and Australia, and two primary oceans, Pacific and Indian. With a coastline extending over 50,000 km – the world's second longest - Indonesia is one of the largest maritime-oriented nations in the world. While mostly bordered by ocean, it shares land boundaries with the neighboring countries of Papua New Guinea, East Timor and Malaysia (Ellicott and Gall, 2003; Fig. 1).

The population is concentrated on a few big islands such as Sumatra, Borneo, Celebes, Java, Lesser Sunda cluster, Molucca cluster and New Guinea. These represent more than 90% of total landmass and Java is the most populous island. Almost all of its islands are located within the Pacific volcanic ring of fire. With 76 presently active volcanos, Indonesia is a country with the highest number of volcanoes in the world. The large number of volcanoes contributes to the high variability of topography along the islands. The margins of the big islands are usually comprised of coastal lowlands in

which the population is mainly concentrated, while the interiors are mountainous and sparsely populated (Kemendagri, 2015).

Figure 1. Map of Indonesia (Ellicott and Gall, 2003)

Indonesia occupies an area at the intersection between four tectonic plates. Combined with existing volcanoes, this results in high risk for earthquakes and tsunamis. The 2004 Indian Ocean tsunami, for example, caused 100,000 casualties in Indonesia alone (Meisl *et al.*, 2006). These kinds of acute natural disasters are of relatively short duration but produce great impacts, comparable to the effects of hurricanes or typhoons events at higher latitudes. Indonesia is relatively safe from the impact of tropical cyclones, due to its proximity to the equator. Cyclone tracks rarely pass over the central portion of the maritime continent, where the population is concentrated (Chang and Wong, 2008).

Nonetheless, Indonesia is at great risk from other types of hydrometeorological disasters, namely drought and flood. Although rarely causing fatalities, both are associated with large financial and property losses (CFE-DMHA, 2015). Drought events cause severe impacts for economic activities and productive sectors that depend on the constant availability of water supply. Furthermore, severe droughts, along with high temperatures, low moisture levels, and presence of biomass, can lead to forest fires, which not only causes significant economic loss, but also great disturbances in air quality (CFE-DMHA, 2015). Significant portions of Indonesia are exposed to flood risks, particularly over areas occupied by rugged terrain where mass wasting events, including flash landslides, can turn out to be fatal (CFE-DMHA, 2015).

As one of the most populous countries in the world (ranked 4th) and, undergoing intense economic development, Indonesia is going through a phase in which urbanization is inevitable. Nevertheless, the traditionally rural activities of agriculture and fishing are still prevalent. In the fourth quarter of 2017, these represented the largest sector of the economy, responsible for 34.3% of the national Gross Domestic Product (GDP), followed by oil and gas production, manufacture industries and large-scale trading respectively (BPS, 2018). The latest available survey, conducted in 2011, indicates that over 30% of the Indonesian land-mass is still defined as agricultural land. The other 50% are forests with less than 20% occupied by other land uses (CIA, 2011). While being the nation's economic backbone, agriculture and fisheries are also very susceptible to hydrometeorological disasters or climate anomalies.

In atmospheric and climate studies, the area centered on Indonesia is often referred to as the maritime continent, consisting of a large number of islands of various sizes. It is a very geographically diverse environment, resulting in a large range of distinct climatic conditions between regions. In general, it has the maritime tropical and rainforest climate, with some inland mountains areas exhibiting highland climate and some regions characterized by tropical savannah climate. During the year, humidity remains high, with relative humidity almost always above 70%. Temperature variability is not significant in the diurnal, seasonal or annual scales, with an average annual range of 25°C to 27°C (World Bank, 2016).

The most important atmospheric parameter to be considered for daily life is precipitation, particularly in the form of rainfall (BMKG, 2012). The occurrence of rain and its variability, be it in short- or long-term scales, has great impact on the activities of people, not only those active in economic sectors directly impacted by precipitation, such as agriculture and water supply, but also for those in areas less directly dependent on precipitation, such as water and aerial transportation, infrastructure, mining industries, fisheries, and others.

2.1.2 Rainfall pattern

With rainfall being the main climatic parameter of interest, many studies were dedicated to investigating the pattern of rainfall in various timescales. Central to those are efforts to understand seasonal variation and identify the time at which rainfall days and intensity reach their peaks and lows.

An important contribution, often referenced by both research and operational projects, are the results described in Aldrian and Susanto (2003). The authors apply a double correlation method and empirical orthogonal function (EOF) analysis to 33 years (1961–1993) of surface observations from WMO registered stations administered by the Indonesian Agency for Meteorology, Climatology, and Geophysics (BMKG) and to a gridded rainfall dataset (Peterson *et al.*, 1998) to show that the annual rainfall patterns differ among three distinct areas: Region A, consisting of South Sumatera to Lesser Sunda region, southern Borneo, Celebes and part of New Guinea; Region B, consisting of northern Sumatra to northwest Borneo; and Region C, consisting of the Moluccas and northern Celebes (Fig. 2). Region A, which contains the island of Java, covers the largest area and concentrates most of Indonesia's population.

Figure 2. The three dominant rainfall regions as proposed by Aldrian and Susanto (2003)

For Region A, precipitation is heavily influenced by the Indo-Australian monsoons, with a wet season from November to March, and drier conditions from May to September. Rainfall over Region B is dominated by the meridional oscillation of the Intertropical Convergence Zone (ITCZ) and exhibits two annual peaks, one around April the other around November. Region C's precipitation is influenced by oceanic processes. It exhibits a peak between the months of May and August and lowest rainfall values between November to February. Region C is located in the eastern part of the Indonesian Through Flow route, with currents bringing surface water from the Western Hemisphere warm pool. During the boreal winter, the oceanic flow brings cooler water from the warm pool to the area, constraining convection. During boreal summer, warmer waters are

advected from the western Pacific into the region, producing more convection. As shown in Fig. 3, the standard deviation of precipitation over Region A has the smallest value of all three areas throughout the year, confirming a coherence of the annual pattern over the area. Region A is often referenced as the “Monsoonal type”, while Region B is called “Equatorial type” and Regional C defined as “Anti-Monsoonal” type. The average peak rainfall amount in all of the regions is around 300 mm per month. The difference of the annual pattern between the three regions is illustrated in Fig. 3.

Figure 3. Annual pattern of the three rainfall regions (Aldrian and Susanto, 2003)

BMKG, based on a data set covering 29 years (1981-2010) and with higher spatial density than the one adopted by Aldrian and Susanto (2003) , proposed an

expansion of the scheme described above with a 4th region - over the Central Celebes and Banggai - that experiences low rainfall throughout the year and an additional 73 relatively small areas where annual rainfall patterns and intensity do not follow those observed in their adjacent areas (BMKG, 2012; Fig. 4).

Figure 4. The three dominant rainfall regions as characterized by BMKG (2012)

2.1.3 Rainfall-related mechanisms

The previous section has explained the relative importance of some processes in affecting annual rainfall patterns in Indonesia, namely the Indo-Australian monsoon, the ITCZ and the phase of the Indonesian Through Flow. There are other atmospheric mechanisms that also affect the occurrence of rainfall from short- to long time-scales.

These mechanisms are responsible for the abrupt variability of rainfall occurring in the maritime continent area.

The diurnal cycle of convection over land and ocean is a key factor that influences other processes, such as radiative transfer, boundary layer exchange, convection, and cloud process. As short-term variability, this mechanism is heavily associated with the convection that occurs over islands in the Indonesia area. It has been found that due to the complex geographical features of the maritime continent, convection is greatly influenced by local forcing mechanisms (Yang and Slingo, 2001). Convection peaks during the afternoon over land and during the early morning over the ocean. In general, the shift in the time of sunset and sunrise is not significant in Indonesia, with a maximum of only 40 minutes in most areas throughout the year. Hence, convection diurnal temporal patterns are fairly constant throughout the year.

This difference in the peak time of convection, along with other factors such as orography of the islands, heterogeneous coastline structure, and differences in land cover, increase the complexity of local convective mechanisms. In general, the land and ocean variation in the area creates a large variation in surface stability. This diurnal cycle convective activity is also related to the land-sea breeze circulation around the coastlines, which together contribute to the water cycle of the area between the inland mountains and the island's coastline. Hadi *et al.* (2002), based on radar data, found that cloudiness is related to the temporal variability of nighttime sea breeze. The intensity of the diurnal cycle (or local) convection can either be intensified or weakened by mesoscale mechanisms. There are different kinds of mesoscale cloud-related processes in the form

of cloud clusters with various lifespans, from several days to intra-seasonal scale. In particular, localized convection over Indonesia is affected by the progression of the Madden-Julian Oscillation (MJO). The MJO is a fluctuation that occurs in the tropical region around the world at sub-seasonal time scale (weekly to monthly). One of its features is cloud band that propagates toward the east along the equator in around 40–50 days (Madden and Julian, 1971). The MJO is weakened as it passes through the maritime continent area, theoretically due to the interaction with the complex atmospheric mechanisms over the area. When the MJO is active over Indonesia, it increases largescale cloud cover over the area, suppressing the diurnal cycle heating, resulting in less rainfall over land. This mechanism could result in a continuous and more spatially-uniform rainfall for several days.

A study by Ichikawa and Yasunari (2006) associates these periods of inactive convection with atmospheric disturbances associated with the passage of MJO. In addition, another study by Tangang *et al.* (2008) attributes an extreme event in the Malaysian peninsula to strong easterly winds associated with a wave response to the MJO. Furthermore, it has been found that MJO is a key factor in the timing of monsoon onset in different regions, including the Indo-Australian monsoon that affects the maritime continent (Hung and Yanai, 2004).

The monsoon cycle is the primary mechanism defining dry and wet seasons in Indonesia. The maritime continent annual monsoon cycle is controlled by the annual variation in temperature between oceans and continents and characterized by the reversal of prevailing surface winds. The Maritime continent is located between the Asian

monsoon zone and Australian monsoon zone. This annual monsoon cycle is comprehensively explained in Chang *et al.* (2005), who discuss the impact of both circulations on the climate of Indonesia. As with the MJO, the annual monsoon cycle influences local convective activities. The Asian winter monsoon and the Australian summer monsoon are responsible for the monsoonal rainfall regime in Indonesia, determining the wet season period in many regions within the maritime continent. The magnitude of the annual monsoon cycle's influence on rainfall is modulated by local or mesoscale monsoonal activities, especially those associated with the meridional shift of the ITCZ (Chang *et al.*, 2005). It has been proposed that the onset of the maritime continent monsoon is related to the El Niño-Southern Oscillation (ENSO) phases and that it could be delayed in an El-Niño year (Robertson *et al.* 2011).

The two main controls of interannual climate variability over Indonesia are the Indian Ocean Dipole Mode (IOD) and ENSO. The IOD is characterized by SST anomalies of opposite signs between the eastern and western Indian Ocean (Saji *et al.* 1999). During the positive IOD phase, SSTs in the western maritime continent region show negative anomalies with higher than average SSTs found in the region during a negative IOD state. Positive IOD conditions are associated with reduced convection and have been shown to contribute to drought risks. These risks are magnified over western Indonesia during periods in which both positive IOD and El-Niño conditions occur at the same time (Ashok *et al.*, 2001). Tangang *et al.* (2008), suggest that the atmospheric structure associated with sudden IOD termination favors the occurrence of extreme weather events in the area.

ENSO - a coupled atmosphere-ocean oscillation with a period ranging from two to seven years - is an important control of the interannual climate variability over the tropical Pacific, and plays a large role in changes to precipitation over Indonesia at these time scales (Hendon, 2003). The oscillation is associated with SST anomalies. ENSO's warm phase, called El-Niño, is characterized by above-average SSTs in Eastern Tropical Pacific while La Niña, the cold phase, is associated with negative anomalies in this area. Under El Niño conditions, western Pacific SSTs decrease, reducing convective activities and increasing the risk of drought in the maritime continent area (Hendon, 2003).

Several studies have analyzed the impact of ENSO phases on Indonesia's climate. Gutman *et al.* (2000) use remote observations from the Advanced Very High-Resolution Radiometer (AVHRR) product to analyze the effects of last century's most intense El-Niño in 1997/1998 and describe decreasing cloud cover, precipitation deficit, increased near-surface temperature over land and vegetation stress. They also link large increases in wildfires to decreases in rainfall associated with anomalous monsoon conditions during the El-Niño event. These findings were later confirmed by efforts that determined the relationship between the Southern Oscillation Index (SOI) and Indonesian rainfall index from sixty-three ground observation sites and conclude that interannual rainfall variability over some regions in Indonesia is controlled directly by ENSO via anomalies in the zonal sea surface temperature gradient (Haylock and McBride, 2001; Hendon, 2003; McBride *et al.*, 2003). Setiawan *et al.* (2017) analyzed a multi-model ensemble and concluded that areas in Indonesia where rainfall is highly related to the Indo-Australia monsoonal cycle – such as southern Sumatra, Java, Lesser Sunda,

Southeastern Borneo, Celebes, and New Guinea - are more susceptible to ENSO-related meteorological drought. Another study by Supari *et al.* (2017b) classifies regions based on either the behavior of seasonal consecutive dry days (CDD) or consecutive wet days (CWD) anomaly during El-Niño events. These classifications indicate the heterogeneity of spatial rainfall distribution over Indonesia and its response to ENSO, suggesting the necessity to verify the tendency of each region within the maritime continent.

2.1.4 Climate change

Natural disasters are common in many parts of Indonesia. As explained previously, the greatest threat from hydrometeorological sources are risks of drought and flood, which can cause other devastating results such as forest fires and landslides. All of them have the potential to generate harmful impacts to the livelihood of large sectors of the population as well as causing environmental damage.

Many studies have highlighted the observed changes in the global and regional climate system. The Fifth Assessment Report by the IPCC (2013) has thoroughly compiled results from various research efforts and summarized them as a reference for policymakers. The next two paragraphs describe some findings from the IPCC report.

The currently ongoing changes in the climate system are undoubtedly attributed to human activity, mainly the addition of CO₂ to the atmosphere through the burning of fossil fuels. Many studies have shown with high confidence that global surface temperature has increased over the past 100 years, with different data confirming the changes to be record-breaking. Observations also show generalized warming in ocean

near-surface temperature, and either decreases or increases in salinity, which tends to be significantly controlled by evaporation and precipitation. The warming has also caused the reduction of ice masses. Ice sheets, permafrost, and mountain glaciers throughout the world are retreating, with an increasing loss rate in the last decade. This loss of ice over land, combined with the ocean's thermal expansion, is leading to rising sea levels, threatening lowland coastal areas worldwide. Arctic sea ice mass and extent are consistently decreasing. Warming is also expected to provoke changes in extreme weather and climate events. It has been observed that either cold and hot extremes have increased globally, manifested as heat waves or cold snaps. As for cyclones, while the impact of climate change is not uniform, it was found that generally the maximum wind speed and precipitation rates would tend to be more intense for any given event.

While impacts related to temperature tend to be fairly well understood, our knowledge is lacking when it comes to the influence of climate change on spatiotemporal patterns of precipitation. The confidence in changes observed during the last century remains in the low to medium range (Fig. 5). This stems, in part, from the scarcity of precipitation records, the spatial and temporal heterogeneity of precipitation and, a lack of detailed mechanistic understanding of forcing mechanisms.

Observed change in annual precipitation over land

1901– 2010

1951– 2010

Figure 5. Maps of changes in annual cumulative observed precipitation (IPCC,2013). Anomalies are relative to the mean of their respective periods. Colored grid boxes represent 70% records availability and at least 20% completed data in the beginning and 10% completed data at the end of the time period. Areas with significant change at the 90% confidence level are shown with a small plus (+) sign.

Indonesia is also vulnerable to the potential impacts of climate change. As a country made up of more than 13,000 islands and with long coastline area in which many cities are usually located, rising sea level could be a serious threat for coastal infrastructure as well as the wellbeing of the affected population (Nicholls and Mimura, 1998). Case *et al.* (2007) identify impacts to sea level rise, human health, water availability, biodiversity and ecosystem, and vulnerability of productive sectors toward changes in climate as the most important climate risks in Indonesia. The issue of water availability and economic vulnerability are highly related to the change in precipitation and its extremes, particularly in the risk of drought and disaster management, as explained in previous sections.

Some notes on the future trends on regional climate dynamics are also discussed in the IPCC report (IPCC, 2013), with some of them related to important controls of the climate in Indonesia, such as monsoon and ENSO. These results are based on the CMIP5 global climate model simulations, in which one of the ensemble members provides input data for this study. In general, models predict an increase in intensity, area, and duration of the global monsoon systems. The Asian-Australian monsoon would experience a change in intensity but this would not be uniformly distributed over the monsoon domain. Projected changes in the Indian Ocean Dipole (IOD) would result in a decrease of precipitation over the western maritime continent region. While the model representation of ENSO and its teleconnections is still lacking, there have been measurable improvements between CMIP3 and CMIP5. Current projections indicate that, due to the

warming-driven increase in water vapor, the associated ENSO related precipitation anomalies would intensify. For Indonesia, this would mean an increase in the probability of severe drought during El-Niño and more rainfall during La-Niña. Models at this time do not adequately reproduce the MJO.

As explained in the previous chapter, studies related to the changing climate in Indonesia are focused on using observations to record alterations to the mean state and trends in extremes. Their primary goal is to provide practical information on how the climate has changed, and these studies are not focused on understanding the dynamics and forcing at the regional scale. The small number of available observations and their sparse spatial distribution hinder our understanding of climate change impacts in Indonesia. The longest available dataset, containing 130 years of rainfall and temperature observations from Jakarta, have been used to evaluate local changes over the Greater Jakarta in the study by Siswanto *et al.* (2015a) described above. Some earlier efforts have made use of more limited data and focused on smaller areas. Examples are the study that found a decrease in cumulative rainfall and an increase in dry spell period over the Brantas river basin in East Java for the last 50 years (Aldrian and Djamil, 2008), and work by Robertson *et al.* (2009) that outlines the lack of spatiotemporal predictability in last 30 years of observed rainfall over the Indramayu district in West Java. Supari *et al.* (2017a) use station data from the whole Indonesia to describe spatiotemporal changes of rainfall and temperature in the last 30 years. Interestingly, they found that the warming is actually quite significant, ranging from 0.18 to 0.3 degree Celsius per decade. Other temperature indices such as extreme hot (cold) days (night) are also increasing. However,

their findings on the rainfall-related indices provide less significant results and high spatial variability. The changes in rainfall and its derivative indices are highly seasonal and depended on process operating at smaller spatial (Supari *et al.*, 2017b).

2.2 Climate modeling in the maritime continent

Efforts on atmospheric and climate modeling on different spatial scales and areas have existed for a long time and have greatly increased during the modern era of high-performance computing (Lynch, 2008). One of the earliest modeling studies dealing with precipitation within the maritime continent was developed by Kitoh and Arakawa (1999). In their study, they investigated the tendency of an atmospheric-only model to overestimate rainfall duration when supplied with boundary conditions from a coupled general circulation model. They found this anomaly particularly prevalent in the tropical area and attributed the cause of this to the inability of the atmospheric model to limit the simulated rainfall because of the lack of SST and cloud feedbacks during precipitation events. One of their recommendations is that caution should be taken in analyzing results from an atmospheric-only simulation forced by coupled GCM output.

In a study by Lau and Nath (2000), ENSO's control on precipitation over the Asian-Australian monsoon region is analyzed using the GFDL R30 GCM with prescribed SST over a 50-year period during the last century. Averaged model results have indicated ENSO related anomalies on the monsoon in the form of variations in precipitation and circulation represented by low and high-level winds. These anomalies also result in the disturbance in radiative fluxes and cloud cover, which further impact the SST in the

Indian Ocean. Kang *et al.* (2002) analyze how GCMs from 11 different modeling centers reproduced the 1997-1998 El-Niño event and found that although models could simulate the precipitation anomalies in the central Pacific quite well, there is little agreement between models, and most showed low skills in representing both the amplitude and spatial distribution of precipitation over the maritime continent region.

Saito *et al.* (2001), based on high-resolution simulations with a 2.5 km spatial resolution over Tiwi island in the maritime continent area using the NHM double-nested numerical model developed by Japan's Meteorological Research Institute, conclude that orographic processes play an essential role in determining cloud merger processes and convective intensity over Indonesia at the diurnal time scale. Authors also call attention to the fact that, at the correct resolution, models are capable of reproducing important dynamic aspects of the island-scale circulation. Collier and Bowman (2004) investigated the diurnal cycle in the tropics by comparing the output from the Community Climate System Model Version 3 (CCSM3) model to satellite-based observations from the Tropical Rainfall Measuring Mission (TRMM). The authors attribute model precipitation biases to the biases in amplitude and phase in the diurnal cycle, which consequently impact the water cycle and energy budgets. Another study further emphasized the importance of local-scale processes, in the form of diurnal cycle that acts as a block for the eastward-MJO, by using a simplified version of HadCM3 and idealized states that resembles maritime continent configurations (Inness and Slingo, 2006).

Much of the modeling research on the maritime continent area is focused on precipitation and its related mechanisms. Most of them indicate a lack of model

capability in properly simulating the occurrence, intensity, and distribution of rainfall. A study that performs a regional simulation using the RegCM3 model found that the main sources of error in the maritime continent are the parameterized convection and land surface schemes, which are proven to significantly control the intensity of rainfall and diurnal cycle processes (Gianotti *et al.*, 2012). Simulations with the MetOffice's UM RCM over the maritime continent area show the dependency of model skill on model spatial and vertical resolution (Love *et al.*, 2011), with larger errors produced by lower-resolution simulations associated with the model's failure to generate a coherent convective response, resulting in biases within the diurnal cycle and long-term precipitation. Schiemann *et al.* (2014) confirm this by further analyzing the biases produced by the same GCM with different spatial resolutions for the maritime continent area. However, they attribute the increase in model skill in simulating mean precipitation to the coastal tilting formulation, which is how the surface boundary conditions (land-sea distribution, land-use, and soil attributes) are represented, in contrast to a more well-represented detailed topography or moisture transport mechanisms. They also attribute the excessive rainfall produced by higher resolution model results to the enhanced moisture convergence related to the intensifying Walker circulation. An attempt to couple an RCM with a regional ocean model (ROM) improved the representation of latent heat and net heat fluxes in the atmosphere, decadal evolution of SST, and upper-layer oceanic thermal structure, but still failed to significantly improve the simulated precipitation over the maritime continent due to the lack of model capability in representing feedbacks such as moisture convergence and convection which are supposed to be induced by previously

mentioned mechanisms (Wei *et al.*, 2014). Hayashi *et al.* (2008) conducted a statistical verification using a threat scoring procedure to compare the performance of two distinct RCMs over different domains. Both models are used in simulations over the western maritime continent area and the mid-latitude area around Japan and the Korean peninsula. Results generally show the RCM performing better at the mid-latitude domain, where authors also note relatively coherent results between the two models. Over the western maritime continent area, the RCMs exhibited lower skill and there is less agreement between models. Hara *et al.* (2009) compared the RCM simulated diurnal cycle precipitation to the cycle generated by a high-resolution GCM with a 20 km spatial resolution. They found that this resolution is sufficient in resolving the topography and local circulations associated land distribution and orographic effects within the GCM simulation. They also compared their GCM simulation with a one-month regional simulation performed using the WRF model forced by National Center for Environmental Prediction (NCEP) global tropospheric analysis data. The comparison shows agreement between the two models, which are verified by TRMM data. The regional simulation using WRF particularly improved the precipitation biases at weekly scales. However, the improvement is only significant over a small part of the domain.

In addition to improvements, studies have also highlighted some limits in regional climate simulations over the maritime continent area. Gao *et al.* (2011) confirm that regional climate simulations using the MM5 model provide a better match to local observations than the reanalysis product used as boundary conditions by the RCM. The authors performed simulations focused over the East Asia summer monsoon area near the

northern part of the maritime continent for the period of 1998 boreal summer, using different convective schemes, land surface models, initialization times and domain locations, each with two variations. The convective schemes used are the Grell scheme and the Kain-Fritsch scheme. Both results from different convective schemes are shown to be consistently improved compared to the coarser forcing data, with simulations employing the Grell convective scheme providing a higher correlation coefficient and lower RMSE value. Another study investigating the diurnal cycle in the maritime continent area has found that the basic diurnal forcing in their regional climate simulations is highly amplified, most notably in the land area and particularly over elevated terrain, meaning that the amplitude of the atmospheric responses to instability caused by radiative source and surface heat flux is significantly overestimated (Teo *et al.*, 2011). Their resulting rainfall is also very sensitive to the presence small land-masses and small-scale topography. It has been argued that these deficiencies come from the inability of the parameterized convection to represent the coupling process of local circulation with convection.

The sensitivity of the RCM simulated atmospheric water cycle strength over the maritime continent area to different physical parameterizations was analyzed by Ulate *et al.* (2014). In the study, several configurations of parameterized physics represented in different regional simulations are performed over the western part of the maritime continent (one of the study's two domain areas, the other being the Indian Ocean), with three-months period simulations starting in October 2009. The study uses 8 different convective schemes, three of which are also utilized in this study (Kain-Fritsch, Betts-

Miller-Janjic, and New Simplified Arakawa Schubert) and three different planetary boundary layer parameterization schemes, with a total of 16 simulations performed. The hydrological cycle strength, which is a function of temperature, moisture, wind, and precipitation, was calculated from the model's output. Results show that different types of parameterization schemes are responsible for different types of biases within the components of the calculated water cycle. For example, in terms of biases in the boundary layer, the Mellor-Yamada-Janjic planetary boundary layer scheme produced consistent dry biases when coupled with all cumulus schemes, while the Yonsei University (YSU) planetary boundary layer scheme causes a dry bias if it is paired with the New Simplified Arakawa-Schubert (NSAS) cumulus scheme, but is improved when paired with the Tiedtke cumulus scheme. On the other hand, there is an unrealistic representation of diabatic heating produced by the YSU scheme that led to further biases in surface evaporation and water convergence flux. The combination of schemes behaves inconsistently over the different investigated domains. For example, simulations with the NSAS scheme tend to produce excessive clouds over the Indian Ocean compared to the western maritime continent domain. In general, the study found that all of the model configurations produce dry biases, which is also a characteristic of the ERA-Interim data used as forcing. The authors suggest that a simulation with parameterization configurations that are chosen arbitrarily might result in a false representation of physical processes. RCM experiments performed by Wang *et al.* (2013) use the WRFchem model and assimilated values of smoke emissions from the Fire Locating and Modeling of Burning Emissions (FLAMBE) dataset to simulate smoke particles transport during the

forest fire event in 2006 associated with a moderate El-Niño. The model successfully simulated the aggregation of various wind-related mechanisms in different scales, from the land/sea-breeze, typhoon, and trade winds.

One example of utilizing an RCM as a tool for simulating future climate projections is the study by Chotamonsak *et al.* (2011). Authors use the WRF model to perform a simulation with 60 km spatial resolution over Southeast Asia, consisting of a historical simulation (1990-1999) and a time slice simulation in the near future (2045-2054). The model displayed low skill in simulating rainfall, primarily during the wet season. Also, the regional simulation tends to produce better results over the mainland, higher latitude, areas compared to regions near the equator. Simulations forced by the IPCC's high emissions A1B scenario showed an increase of precipitation in the future but the authors acknowledge that such projections have high uncertainty (Chotamonsak *et al.*, 2011).

2.3 Regional climate modeling practice

RCMs have been an option for limited area simulations, often also referred to as downscaling. In general terms, they are used to simulate smaller-scale atmospheric processes which could not be resolved by lower resolution global models. The expectation is that RCMs will produce a better representation of the climate in a specific area compared GCMs or reanalysis products that provide RCMs their boundary conditions (Leduc and Laprise, 2008). Studies dedicated to examining the quality and the capability of RCMs often used the term “added value” as a representation for any

improvement that might result from the regional simulations (Lim *et al.*, 2011; Di Luca *et al.*, 2012; Lee *et al.*, 2014).

Giorgi (1990) is among the earliest studies to conduct and analyze output from simulations with a limited area atmospheric model. His research introduces the nesting procedure in which output from two global model simulations, using a same global model (Community Climate Model V1 - CCM1) but different methods of spherical harmonic truncation (R15 and T42), is fed into an RCM (MM4) as the forcing boundary conditions. Results indicated that several parameters, including temperature, humidity, and precipitation, are simulated well and that, compared to the global simulations, the RCM provided a more realistic representation of the local climate. The author attributes this improvement to the more realistic topography and better representation of spatial variability in the MM4.

Many other studies confirm advantages of RCMs. Wang *et al.* (2004) summarized them in their study and highlight their capability in reproducing monthly, seasonal, and climate extremes. They argued that RCMs are important tools and provide better seasonal and climate change impacts predictions. Nonetheless, they also noted that the accuracy of the regional scale output greatly depends on the quality of its driving datasets. Laprise (2008) concludes that RCMs are a relatively affordable option in a limited computational environment, and advantageous for research groups lacking in those capacities. However, he also acknowledges some limitations in the practice, particularly related to the dependencies on the forcing boundary conditions, model stabilization period and configuration issues, all which could affect the likely added

value. Murphy (1999) compared dynamical downscaling (based on RCMs) to statistical downscaling methods. In general, results show that higher spatial resolution leads to a better representation of some processes and a potential increase in projection skill. However, the only way to correct biases in the results is to anticipate the systematic errors in the model itself, in contrast to the option of providing a better observational calibration in the statistical downscaling approach. While both of them are often treated as separated techniques, incorporating statistical procedures to regional simulation results could, in a practical way, increase the realism of the simulated climate (Murphy, 1999).

Rummukainen (2016) discusses how regional simulations can provide added values. From the modeler's perspective, one of them is how the surface characteristics such as topography, coastlines, and land-uses are represented better in the regional scale, resulting in more realistic boundary conditions for the simulation. This is also related to the point of view of a user in which the increased resolution itself is often what is expected, and the model's performance in resolving the physics is increasing the chance of capturing the phenomenon that can hardly be detected by simple interpolation processes. RCMs also allow the inclusion of some mechanisms, such as lake models, urban processes and more sophisticated vegetation feedback, too computationally expensive for most coupled global climate modeling efforts (Rummukainen, 2016).

Lim *et al.* (2011) used an RCM in an analysis of summer precipitation in the southeastern United States and concluded that the regional model results provided a better representation of spatial distribution and monthly cumulative precipitation, reduced the wet bias, and lowered RMSE, compared to its forcing NCEP/DOE R2 reanalysis data.

Di Luca *et al.* (2012) specifically addressed the issue by employing the “Big Brother Experiment” approach to determine the relative contribution of better resolution in the climate statistics. The strategy is adopted as a means of comparing the two simulation results with identical spatial resolution and is done by running a GCM simulation (“big brother”) and an RCM simulation (“little brother”) with the same configuration. The RCM simulation is forced by a low-resolution boundary condition that is obtained by filtering out the GCM fine-scale data. This filtering is assumed to reproduce what would happen if the RCM was driven with the lower resolution GCM. Hence, there is no need for an observational comparison, because the use of the same model and same physics reduced the errors that are associated to the model itself, and the difference between the “big-brother” and “little brother” can be attributed to nesting technique only. They found that the potential added value in a regional simulation is significantly higher for short-term results and phenomena associated with the small-scale processes, such as convection. In addition, although the biases from the input forcing data are often transferred to the regional simulation, it does not increase the mean biases in a significant manner, meaning that although a GCM might already perform well in their respective scale, a downscaling procedure could still add value to the spatial and temporal distributions of parameters of interest (Berg *et al.*, 2013). Lee *et al.* (2014) implemented a double-nesting procedure - a practice of employing a second nested domain with a higher resolution inside the first domain that is also treated as the boundary condition simultaneously - and found that higher resolution experiments resulted in significant improvement in simulated precipitation and temperature over East Asia in general (which

is the first nest of the regional simulation with 50 km resolution) and Korean peninsula in particular (which is the second nest with 12 km resolution). The output with the highest resolution also displayed the best performance in simulating primary features of the upper atmospheric structure and their spatial distributions.

Aside from those facts, there are some conditions to be noted in utilizing RCMs as tools for reproducing climate in the past or for forecast implementations. One should be careful with the domain placement and size for the coverage of mesoscale features, while not letting the domain size to be too large as the result might diverge significantly from the driving data unless analysis nudging is performed (Leduc and Laprise, 2008). Other aspects such as physics schemes and vertical resolutions are worth paying attention to due to their potential effects on parameters of interest (Roeckner *et al.*, 2006; Bukovsky and Karoly, 2009).

One of the most widely used RCMs, also the one adopted in this study, is the WRF model (Skamarock, 2005). It is developed and maintained by the National Center for Atmospheric Research (NCAR) as a mesoscale numerical weather prediction system for atmospheric research and operational forecasting. The simple, easy-to-use, and open-sourced nature of the model are some reasons for many studies to utilize it as a primary tool for climate downscaling. There have been several studies suggesting added value from WRF utilization. WRF has been found to reproduce the spatial distribution of precipitation and temperature over the western United States quite well (Caldwell *et al.*, 2009). A study also mentioned its capability to add significant details to surface temperature and precipitation if forced by ECMWF reanalysis data, particularly when it

comes to geographical distribution, wet-days frequency and extreme precipitation cases (Heikkilä *et al.*, 2011). Other research performed future climate change analyses by forcing WRF with climate projection datasets (Salathé *et al.*, 2010; Chotamonsak *et al.*, 2011). The developers of WRF have acknowledged the diverse group of WRF users and try to accommodate the demands from different fields of research with various efforts, such as the implementation of methods and software specified for climate simulation diagnostics and increases in the capability of its preprocessor to accommodate the ever-increasing global model products (Leung *et al.*, 2006). In general, RCMs are commonly found to produce added value compared to its original coarser forcing, but the degree of the added value itself varies among models, variables, scales, areas, tuning configurations, boundary conditions, parameterizations, and the desired purpose of the outcome.

Chapter 3: Objectives and Methodology

3.1 General objectives

As presented in Chapters 1 and 2 above, there is evidence for past changes in rainfall patterns and extremes over Indonesia. Change in future rainfall tendencies is also to be expected for the area. In this study, considering that the islands of Indonesia and/or their topography in the maritime continent are not well represented by the spatial resolution of global climate models (GCMs), we evaluate the utility of using precipitation from RCM simulations as a dynamical downscaling strategy for the region.

The two general goals of this study are, first, to verify if RCM simulations provide a better representation of observed precipitation over Indonesia than GCMs, and second, use the information coming from the first goal to make predictions of future changes in rainfall based on RCM simulations.

Taking into account that convective rainfall is the most common type of precipitation in the maritime continent region (Qian, 2008), and that variability associated with ENSO has been highlighted as one of the most important factors controlling the occurrence of a long-term hydro-meteorological disasters (such as droughts) in the area (Gutman *et al.*, 2002; Hendon, 2003), the first goal is addressed by experiments that gauge how different cumulus parameterization schemes impact RCM skill in reproducing observed precipitation patterns under different ENSO phases.

3.2 Data

3.2.1 Reanalysis

Data from the ERA-Interim (Dee *et al.*, 2011) reanalysis are used as forcing for the historical regional simulation convective parameterization sensitivity experiments. The adopted ERA-Interim dataset is provided by the European Center for Medium-Range Weather Forecast (ECMWF), with T255 (approximately $0.8^{\circ} \times 0.8^{\circ}$ or 80 km) horizontal resolution and 60 vertical levels. This reanalysis product has been widely used as a primary reference dataset for various climate analyses, and most importantly, several modeling experiments have also been using it as a boundary condition for regional climate simulations. For example, it is the most commonly used dataset for the CORDEX framework, as introduced by Giorgi *et al.* (2009), including the CORDEX-Africa project (Nikulin *et al.*, 2012), as well as other regional simulation studies (Kendon *et al.*, 2012; Rauniyar and Walsh, 2013). The recent CORDEX-Southeast Asia cooperative work also used the ERA-Interim reanalysis dataset as forcing for the RegCM4 regional model (Juneng *et al.* 2016; Ngo-Duc *et al.* 2017; Cruz *et al.* 2017).

The following ERA-Interim data are used as forcings. 2-Dimensional variables: surface pressure, 2-meter dewpoint temperature, 2-meter temperature, 10-meter wind field, mean sea level pressure, sea surface temperature, skin temperature, 4-layers soil temperature, and 4-layers volumetric soil moisture. 3-Dimensional variables: geopotential height, relative humidity, specific humidity, temperature, wind field.

3.2.2 CMIP5 future climate projection datasets

For the purpose of producing future projections of high-resolution precipitation, the RCM requires forcing information from GCMs. In this study, some RCM experiments are forced by future climate projections generated by the Max Planck's Institute Earth System Model with Medium Resolution (MPI-ESM-MR). The model is one of the several global climate models within the CMIP5, used by the IPCC in their 5th Assessment Report as a reference for future climate states (IPCC, 2013). The atmospheric components that are used as boundary conditions for future simulations come from the ECHAM6 (Stevens *et al.*, 2013) dataset. The SST data is also sourced from the MPI-ESM-MR CMIP5 model. The ECHAM6 forcing data has the spatial horizontal resolution of T63 (approximately 1.8°x1.8°) and 96 vertical levels. Utilized results come from simulations forced by the Representative Concentration Pathway 8.5 (RCP8.5) scenario, the RCP predicting the largest increase in radiative forcing, with the CO₂ equivalent atmospheric concentration of almost 650 parts per million per volume (ppmv) by the year 2050.

3.2.3 Observational dataset

The rainfall observation dataset used to verify regional simulations' skill in reproducing historical rainfall is the Climate Hazards Group Infrared Precipitation with Station (CHIRPS) v2.0 by the Climate Hazards Group of the University of California, Santa Barbara (Funk *et al.*, 2015). This is a relatively recent gridded observational set

that combines infrared satellite measurement (including values from the Tropical Rainfall Measuring Mission 3B42 or TRMM 3B42), model data from the National Oceanic and Atmospheric Administration's (NOAA) Climate Forecast System (CFSv2), and surface rain gauge observation data. Developed for analysis of climate extremes and drought early warning, the CHIRPS set provides daily means on a $0.05^{\circ} \times 0.05^{\circ}$ (around 5x5 km) spatial grid. These spatial and temporal resolutions are significantly higher than most available precipitation products and CHIRPS data have been used by previous studies focusing on the maritime continent area (Hermawan *et al.*, 2015; Rustiana *et al.*, 2017).

A recent study by Rauniyar *et al.* (2017) provides a comprehensive comparison between different gridded precipitation datasets, including CHIRPSv2. The study outlines that no single dataset is coherently better in all aspects analyzed. As an example, CHIRPS outperforms other datasets at the seasonal scale and offers the best spatial distribution of daily values, but is only the second-best in its accuracy in the monthly scale. Another example is in how CHIRPS underestimates the MJO signal by around 40%, higher than the compared ~20% underestimation of the best performing sets, such as TRMM, but better than other products that underestimate the signal by about the 60%. Overall, among post real-time products - those not dedicated to describing a particular event with high temporal resolution -, the CHIRPS dataset provides the best estimates of observed rainfall for the goals of this project.

3.3 The WRF model and cumulus physics

All regional simulations in this study are conducted with the Weather Research and Forecasting model (WRF, Skamarock et al., 2005). The WRF is a non-hydrostatic numerical model using the third-order Runge-Kutta time stepping approach. WRF has the capability to simulate mesoscale atmospheric processes in the short and long-term and supports parallel processing or job-sharing in multiple processors. Here, version 3.9 of the model's dynamical core is used (Skamarock *et al.*, 2005). WRF has been widely adopted as a tool to perform regional climate simulations. Lo *et al.* (2008) have investigated several possible methods to conduct regional climate simulations using WRF by comparing the different periods of integration and initializations as well as the utilization of three-dimensional nudging. Bukovsky and Karoly (2009) were some of the first to investigate long-term seasonal precipitation simulated by WRF. Several studies have utilized WRF to reproduce the maritime continent area climate (Hayashi *et al.*, 2008; Hara *et al.*, 2009; Chotamonsak *et al.*, 2011; Gao *et al.*, 2011). In these earlier efforts, the model did not offer a good representation of observed precipitation in the region.

As with other RCMs, WRF provides packages of parameterized physics schemes that are used to represent different sub-grid scale processes, including microphysics schemes, longwave and shortwave radiation schemes, surface layer schemes, land surface schemes, and planetary boundary layer schemes. As explained above, this study's focus is on the response of precipitation to distinct commonly used cumulus parameterization schemes.

Four cumulus schemes are analyzed. The first is the Kain-Fritsch (KF) scheme (Kain, 2004, “cu_physics = 1” in the model’s namelist). This scheme employs deep convection (also including shallow convection) using a mass flux type approach with downdrafts, updrafts, entrainment, and detrainment. The simulated cloud would persist in convective time scale and the detrainment includes all phases (cloud, snow, ice, rain).

The second is the Betts-Miller-Janjic (BMJ) scheme (Janjic, 1994; Janjic, 2000, “cu_physics = 2” in the model’s namelist). This is an adjustment-type scheme where the moisture column is adjusted towards a well-mixed profile. The BMJ scheme is a modification of previous Betts-Miller scheme which introduces the cloud efficiency mode that allows more chance of unsaturation, reducing the possibility of unrealistic precipitation. It does not use any explicit cloud updraft or downdraft nor explicit cloud detrainment.

The third is the Grell-Freitas (GF) scheme (Grell and Freitas, 2013, “cu_physics = 3” in the model’s namelist). It is an improvement on the Grell-Devenyi scheme (Grell and Devenyi, 2002) that tries to smooth the transition to cloud-resolving scales. It uses multiple closures such as CAPE removal, moisture convergence, cloud base ascent and quasi-equilibrium approach. The updraft and downdraft processes in this scheme are explicit, and it includes cloud and ice detrainment.

The last is the New Simplified Arakawa-Schubert (NSAS) scheme (Han and Pan, 2011, “cu_physics = 14” in the model’s namelist). It is also a quasi-equilibrium scheme with deep and shallow components, with a new mass-flux type shallow convection compared to the previous Simplified Arakawa-Schubert scheme (Pan and Wu,

1995). It employs simple clouds with no random top and momentum transport with the pressure-gradient term.

3.4 Experiment design

Experiments require a high-performance computing environment since the RCM is a rather expensive tool in terms of computational resources. All simulations are conducted in the Oakley Cluster of the Ohio Supercomputer Center (OSC). Simulations are done based on a one-way nesting method that processed the reanalysis or CMIP5 GCM forcing data into 20 km grid resolution. The domain creation processes are performed using the *geogrid* function within the WRF package, and the surface terrestrial data used for this configuration is the USGS (United States Geological Survey) Global Digital Elevation Model 30 Arc-Second Elevation (GTOPO30) with 30 seconds (about 800 m) spatial resolution (USGS, 2016). For the simulations, USGS data are interpolated into the 20 km RCM resolution. The coverage of the domain includes the whole maritime continent area, extending from the Philippines in the north and northern Australia to the south. The boundaries are around 87.5°E to 157.5°E and -21°S to 21°N (Fig. 6). The wider area of the domain is chosen in order to avoid effects of boundary error on the area of interest (Seth and Giorgi, 1998). Forcing data from both reanalysis and GCM climate projection have 6-hour temporal resolution.

Figure 6. Domain area for the all of the simulations used in this study. The grid cells shown here are representing the scale of the regional model at 20 km spatial resolution.

3.4.1 Reanalysis forced historical simulations

ERA-Interim reanalysis data are used to force the RCM in three, yearlong historical simulations. Forcing years are chosen in order to represent positive, neutral and negative ENSO phases. Table X1 shows the Oceanic Niño Index of the Niño 3.4 zone, as provided by the Climate Prediction Center of NOAA (CPC, 2018). 2013 is chosen as the neutral ENSO year, while 2015 and 2010 are chosen as representatives of strong El-Niño and La-Niña conditions respectively. While negative indices show that La-Niña conditions were present throughout 2011, 2010 is chosen due to the intense La-Niña

anomalies during the second half of the year and also because during this year Indonesia experienced notorious regional crop failures due to the high rainfall and floods. The event is called the “*Kemarau Basah 2010*”, or literally translated, the “2010 Wet Dry-season”.

Year	DJF	JFM	FMA	MAM	AMJ	MJJ	JJA	JAS	ASO	SON	OND	NDJ
2010	1.5	1.3	0.9	0.4	-0.1	-0.6	-1.0	-1.4	-1.6	-1.7	-1.7	-1.6
2011	-1.4	-1.1	-0.8	-0.6	-0.5	-0.4	-0.5	-0.7	-0.9	-1.1	-1.1	-1.0
2012	-0.8	-0.6	-0.5	-0.4	-0.2	0.1	0.3	0.3	0.3	0.2	0.0	-0.2
2013	-0.4	-0.3	-0.2	-0.2	-0.3	-0.3	-0.4	-0.4	-0.3	-0.2	-0.2	-0.3
2014	-0.4	-0.4	-0.2	0.1	0.3	0.2	0.1	0.0	0.2	0.4	0.6	0.7
2015	0.6	0.6	0.6	0.8	1.0	1.2	1.5	1.8	2.1	2.4	2.5	2.6

Table 1. Cold and warm episodes in the Niño 3.4 Region based on the Oceanic Niño

Index (ONI) calculated by NOAA Climate Prediction Center.

As explained earlier, historical simulations test the sensitivity of RCM modeled precipitation to four cumulus parameterization schemes. The simulations are done by initializing each process separately. There are three years and four different cumulus schemes, hence, 12 yearlong simulations are conducted in total. The regional model performance is then compared with gridded precipitation from CHIRPSv2 (Fig. 7).

Figure 7. Diagram illustrating the flow process of the historical simulations.

Each simulation is initiated from the date of December 1st of the previous year, allowing for a 30-day spin-up time in order to allow the WRF to reach “climate mode” (Zhong *et al.*, 2007). Given the relatively long experiment durations, SST boundary conditions are updated daily with values also sourced from the ECMWF ERA-Interim dataset. Other physics parameterizations not related to convection are selected based on their adoption by previous relevant RCM experiments within or around the maritime continent area and/or South East Asia. These include: The WRF-Single-Moment 6-class (WSM-6) microphysics scheme (Hong and Lim, 2006); the Yonsei University (YSU) planetary boundary layer parameterization (Hong *et al.*, 2006); the RRTMG shortwave and longwave radiation physics scheme (Iacono *et al.*, 2008); and the Eta similarity based on Monin-Obukhov-Janjic surface layer scheme (Janjic, 1994). The Noah LSM (Ek *et al.*, 2003) is used as the land surface model for the simulations.

3.4.2 GCM forced historical and future climate simulations

The Betts-Miller-Janjic cumulus scheme - which generated the best representation of precipitation in the reanalysis forced historical simulations - is the only one adopted in the WRF simulations forced by boundary conditions coming from the ECHAM6 GCM. Other than the single cumulus parameterization, all GCM-forced regional simulations utilize the same configuration and spin-up time as the reanalysis-forced RCM experiments. Simulations are divided into three groups: Baseline, Near Future, and Far Future. In the Baseline simulations, WRF is forced by boundary

conditions from historical ECHAM6 experiments. Three yearlong baseline simulations are conducted, each forced by GCM climate states representing distinct ENSO phases. The near and far future experiments last five years each and are forced by GCM output from years 2036 to 2040 and 2096-2100 respectively (Fig. 8).

Figure 8. Diagram illustrating the flow process of GCM-forced WRF simulations.

As ENSO variability in the MPI-ESM-MR historical simulation does not track observations (Fig. 9), year selection for the baseline simulations is not directly based on observed SSTs or real-world ENSO indices. Instead, MPI-ESM-MR SST patterns over the tropical Pacific and the daily evolution of model-derived area-averaged SST anomaly over the Niño 3.4 region are compared to observations to identify years when GCM SST anomalies exhibit patterns and values associated with distinct ENSO conditions (Fig. 9 and Fig. 10). This led to the selection of model years 2007, 2012 and 2014 as representatives of La-Niña, neutral and El-Niño states respectively.

Mean SST Anomaly - MPI-ESM

Figure 9. Spatial pattern of the 1-year daily-averaged SST anomaly over the Pacific Ocean. The first row shows three different years associated with three distinct phases of ENSO in observation data (Neutral ~ 2013, La-Niña ~ 2010, El-Niño ~ 2015). Last three rows show different years of the MPI-ESM-MR data from 2006 to 2016. Units are in degrees Celsius ($^{\circ}\text{C}$). Observed SST anomaly data come from NOAA's Optimum Interpolation Sea Surface Temperature (OISST) v2 (Reynolds *et al.*, 2002).

Figure 10. Area-averaged daily SST anomaly of the Niño 3.4 Region. Bold lines show three different years associated with three distinct phases of ENSO in the OISSTv2 observation data (Black ~ Neutral ~ 2013, Blue ~ La-Niña ~ 2010, Red ~ El-Niño ~ 2015). Other lines show different years of the MPI-ESM-MR data from 2006 to 2010 (left) and from 2011 to 2016 (right).

Chapter 4: Results and Discussion

The results and discussion section will be organized as follows: First, the sensitivity of RCM derived precipitation to different convection parameterizations is described. Then, the impacts of different ENSO phases on RCM precipitation are identified and estimates are made of the added value from the regional climate model results in simulating past precipitation when compared to available historical observations. The information obtained by the above efforts, including the identification of biases and best performing parametrizations, is used to generate and interpret regional simulations using future GCM projections from the CMIP5 dataset over two different time slices during the 21st-century.

4.1 Historical simulation

The main purposes of historical simulation experiments are to determine the best cumulus scheme to be used for the domain area as well as evaluate the response of regional simulation to different ENSO phases. The focus of the evaluation is on the biases in seasonal rainfall and differences in the annual rainfall pattern.

To determine model skill in reproducing precipitation at the seasonal scale, the daily rainfall data from three years (2010, 2013, 2015, each representing an ENSO phase) from the CHIRPS observations, ERA-Interim reanalysis and WRF RCM output are

aggregated into seasonal rainfall values and temporally averaged to generated mean seasonal rainfall maps (Fig. 11).

Figure 11. Seasonal rainfall for the historical experiments. First row, CHIRPS observation data; second row, ERA-Interim reanalysis; third to the sixth row, RCM results using the KF, BMJ, GF, and NSAS parameterizations respectively. Each column indicates different seasons (from left to right - DJF, MAM, JJA, SON). Units shown are millimeters.

The seasonal rainfall spatial patterns indicate that RCM results tend to produce more extreme dry and wet values compared to the forcing reanalysis data. A noticeable feature is that RCM precipitation, for all evaluated convective parameterizations, is more sensitive to areas of elevated topography than the reanalysis, suggesting that the increase in spatial resolution results in better simulation of rainfall associated with the orographic effect, a feature identified in previous studies (Giorgi and Bates, 1989; Lim *et al.*, 2011; Berg *et al.*, 2013). Two parameterizations, KF and GF, show a tendency for extreme overestimation of the simulated rainfall. The overestimation is prevalent especially in large land masses such as Borneo and New Guinea. Both schemes also show clusters of high rainfall during summertime - DJF in the southern hemisphere and JJA in the northern hemisphere. This could indicate that these parameterizations overestimate precipitation processes associated with the shift of the ITCZ and the Indo-Australian monsoon.

Differences between observations, the reanalysis and RCM results are calculated as biases in percent and shown in Fig. 12. Since observations are only available over land, the biases are also plotted only over the land area.

Seasonal Rainfall Bias - ERA-Interim - 3-year Average

Figure 12. Biases, in percent, of seasonal rainfall for the historical experiments and reanalysis. First row, difference between ERA-Interim and CHIRPS. Second to the fifth row, following the same sequence as Fig. 11, difference between RCM results produced by selected parameterizations and CHIRPS. Each column indicates different seasons.

The bias analysis underscores the high amount of rainfall produced by KF and GF schemes (Figs. 11 and 12, rows 2 and 3) and shows that both almost consistently produce extreme overestimation throughout Indonesia. The NSAS scheme also overestimates precipitation values in most areas throughout the year, but its anomalies are smaller. These different responses between convective physics schemes are expected and

are also documented in some previous studies utilizing multiple cumulus schemes within their experiments (Kim and Wang, 2011; Ulate *et al.*, 2014; Zeyaeyan *et al.*, 2017). The RCM output showing lower bias, comparable to those of the reanalysis, comes from the BMJ parameterization (Fig. 12, row 3). The area-averaged biases over the whole domain are displayed in Fig. 13.

Figure 13. Area-averaged biases in seasonal rainfall for the historical experiments. Each marker represents different datasets according to the legend. Bars and vertical lines crossing the markers are the range of the 95% confidence interval of the corresponding data point.

The BMJ scheme generates the lowest mean seasonal bias (8.91%), smaller than the reanalysis bias (13.61%) and markedly lower than that of the NSAS scheme

(26.57%), the second best performing parameterization. Simulations using the KF and GF schemes overestimate average seasonal rainfall by 54% and 68.41% respectively. The BMJ parameterization also shows lower biases than the reanalysis for all but the September-October-November (SON) season, but the differences between them during this period are within the margin of error of the analysis (Fig. 13). Overall, BMJ RCM simulations provided added value by either outperforming or, in the SON case, matching the reanalysis skill. The BMJ results, based on both spatial patterns and area-average rainfall, also provide the lowest bias compared to all other parameterizations. Other studies have adopted the BMJ cumulus scheme for RCM simulations over areas near the maritime continent region, including in Australia (Evans *et al.*, 2012), Thailand (Chotamonsak *et al.*, 2012), Java island (Kurniawan *et al.*, 2014), and the Indo-Pacific region (Fonseca *et al.*, 2015).

In order to discuss different responses from different regions within Indonesia, results are averaged over a number of primary islands and their surrounding areas. These are: Sumatra, Java, Borneo, Celebes, Lesser Sunda, Moluccas and New Guinea. This division is not systematically based on climatological characteristics but could be quite relevant for inferring some information related to climate features. Biases of each region are illustrated in Fig. 14. In general terms, these regionalized results follow domain-wide trends, with RCM simulations tending to overestimate precipitation and KF and GF experiments showing larger biases than BMJ and NSAS results. There are though, noteworthy regional differences, including the fact that the BMJ simulations do not outperform NSAS experiments in all areas. Also noteworthy is that over Java and Lesser

Sunda, where rainfall is influenced by the Indo-Australian monsoon, bias variability between different parameterizations (excluding KF) is relatively low compared to other regions presenting either “equatorial” or “local” type rainfall (see Chapter 2 for classification). Also, if only the schemes with the best skill are considered (BMJ and NSAS), results indicate the sensitivity of simulated precipitation to land/ocean surfaces, with simulations underestimating rainfall over the ocean-dominated Moluccas area and greatly overestimating rainfall over New Guinea, an area occupied mostly by land. Such difference in response between land and sea was discussed in an RCM-based analysis of diurnal rainfall in the maritime continent. It was suggested that the badly represented geographical and coastline complexity at sub-grid scale might cause an abrupt transition between land and sea boundaries, which led to an inability of rain to propagate appropriately across different surface types (Teo *et al.*, 2011).

Figure 14. Area-averaged value of the biases in annual rainfall over different regions for the historical experiments. Vertical lines crossing the markers are the range of the 95% confidence interval of the corresponding data point.

When it comes to the magnitude of monthly precipitation over land, the best performance among RCM simulations continues to be seen in the BMJ experiments (Fig. 15), but in terms of the temporal correlation to observations, no RCM simulation offered a better representation of the annual rainfall pattern than the reanalysis. The correlation coefficient between ERA-Interim values and observations is 0.95, with RCM results providing slightly smaller values of 0.88, 0.84, 0.88, 0.85 for the KF, BMJ, GF, and NSAS schemes respectively. As with the biases of seasonal values explained above, the

root-mean-square-error (RMSE) of the KF and GF cumulus schemes is higher, with respective values of 119.4 and 166.8 mm. Next lowest is the NSAS scheme with 50.2 mm and then the BMJ scheme with an RMSE of 25 mm. All of them are higher than 14.7 mm, the ERA-Interim RMSE. The smaller RCM correlation coefficients and larger RCM RMSEs differ from other studies (Lim *et al.*, 2011; Lee and Hong, 2014), in which RCM results are found to have higher correlation and lower RMSE values when forced with a reanalysis boundary condition. A possible cause is discussed later in this text.

Figure 15. Area-averaged value of monthly rainfall for the historical experiments. Each line represents different datasets as explained in the legend. Only the ERA-Interim values show 95% confidence interval wide enough (average ± 8.4 mm) to be represented graphically (gray shade). RCM RMSEs have average 95% confidence intervals of ± 1.07 mm.

The field correlation between simulations, reanalysis and CHIRPS observations are calculated and shown in Fig. 16. ERA-Interim data show relatively larger field correlation values than all RCM results, meaning the rainfall spatial distribution from

reanalysis is better than that of the RCM. This is perhaps understandable, considering that RCM rainfall (Fig. 11) is very sensitive to topography by overestimating rainfall in regions with higher elevation, while ERA-Interim data shown less response towards topographical variability.

Figure 16. Field correlation value of each dataset in different months for the historical experiments. Each marker and line represents different datasets, distinguished by colors and explained in the legend. Bars and vertical lines crossing the markers are the range of the 95% confidence interval of the corresponding data point.

Figure 17. Values of the correlation coefficient (top) and RMSE (bottom) based on monthly rainfall of each dataset in different regions for the historical experiments. Each marker represents different datasets, distinguished by colors and explained in the legend. Bars and vertical lines crossing the markers are the range of the 95% confidence interval of the corresponding data point.

Correlation coefficients and RMSEs are also calculated for the previously presented main island regions (see Fig. 14) and shown in Fig. 17. Correlation coefficient values of RCM results in almost all regions are lower than those of the reanalysis, showing uniform response throughout the domain area. A similar tendency is also seen in the RMSEs with higher RCM errors in almost all regions. There is no specific consistency in the variability between the RCM results for the value of correlation coefficient and RMSE over different areas, hence it cannot be concluded that one cumulus scheme is consistently better in representing the temporal annual pattern of rainfall.

In order to determine the capability of the RCM in simulating rain events, seasonal number of rainy days are calculated and shown in Fig. 18. ERA-Interim overestimates rainfall days in most areas. According to Kitoh and Arakawa (1999), this is due to the fact that precipitation events in atmospheric GCMs (on which ERA-Interim results are heavily dependent) have the tendency to persist for longer than observed ones due to the poor representation of SST and cloud-radiation feedback by the relatively low GCM spatial resolution. The RCM results, however, provide varying responses. Overall, RCM results still produce overestimation. Nonetheless, there are some areas in which biases are smaller than those of the reanalysis. The area average of biases in the number of rainy days is shown in Fig. 19. The lowest biases are shown by the simulations with the KF scheme. However, considering the overestimation produced by that scheme in seasonal rainfall, it might not be the most appropriate representation, as the consequences

would be occurrences of high or extreme rainfall days (less amount of days, more rainfall intensity). The second lowest biases are shown by the BMJ cumulus scheme, which is also the one that provided the lowest biases in seasonal rainfall as explained above. These patterns are consistent for all seasons.

Figure 18. Number of rainy days per season for the historical experiments. First row, CHIRPS observations; second row, ERA-Interim reanalysis; third to the sixth rows, RCM results using the KF, BMJ, GF, and NSAS schemes respectively.

Figure 19. Area-averaged values of biases in the number of rainy days for the historical experiments. Each marker represents different datasets according to the legend. Bars and vertical lines crossing the markers are the range of the 95% confidence interval of the corresponding data point.

Additional relevant precipitation-based indices are also calculated. They are: consecutive dry days (CDD) or dry spell, consecutive wet days (CWD) or wet spell, and extreme rainfall - days with rainfall exceeding 50 mm or R50. These indices are based on the analysis by the Expert Team on Climate Change Detection and Indices (ETCCDI) documented in Zhang *et al.* (2011). At the seasonal scale, CDD values can be used as an

estimate of drought risk. CWD results can be used to estimate the probability of flood or soil oversaturation and the R50 index is the main indicator of flash flood risk.

Following the same procedure described above, seasonal indices based on RCM experiments and ERA-Interim reanalysis are calculated for each grid point and compared against CHIRPS observations. Area averaged indices bias are presented in Fig. 19. The comparison is shown in Fig. 20. Most RCM results are better at representing CDD and CWD, as is seen in the number of rainy days, compared to the ERA-Interim data. In addition, two cumulus schemes, BMJ and KF, consistently provide lower biases in calculated CDD and CWD values than the other two, which are, again, showing the same pattern as seen in the number of rainy days. The calculated values of R50 in the RCM results, however, show no distinct tendency of improvement compared to the reanalysis and no particular scheme performs better than the other when it comes to this index. Extreme rainfall in the maritime continent is a phenomenon often associated with rapid convection at small spatial scales (Strachan, 2007) and these events are likely not captured by the spatial resolutions of neither ERA-Interim or RCM simulations in this series of experiments.

Figure 20. Area-averaged value of the biases in various climate indices for the historical experiments. Each marker represents different datasets according to the legend. Some visible vertical lines crossing the markers are the range of the 95% confidence interval of the corresponding data point.

In order to identify RCM behavior under different ENSO phases, the rainfall tendency in each year is investigated. This time, seasonal rainfall values are calculated separately for each year, with 2010, 2013, and 2015 representing La Niña, neutral and El Niño conditions respectively. Results are shown in Fig. 21. Overall, the BMJ scheme shows higher skill (lower biases) compared to other cumulus schemes over different seasons and different ENSO phases. Generally, both RCM results and ERA-Interim data show lower skill during SON compared to other seasons, as previously seen in Fig. 13. Also, both RCM and reanalysis display higher biases for all seasons during El-Niño (Fig. 21, top). While RCM and ERA-Interim results show similar patterns when averaged over all Indonesia, they differ in their regional response (Fig. 21, bottom). This is most likely

due to the different primary precipitation mechanisms affecting those regions and requires further investigation.

Figure 21. Area-averaged value of the biases in seasonal rainfall over three ENSO phases (top) and comparison of average biases in seasonal rainfall from the ERA-Interim and BMJ dataset over different ENSO phases (bottom). Bars and vertical lines crossing the markers are the range of the 95% confidence interval of the corresponding data point.

In addition to biases in seasonal rainfall, it is also important to verify if RCM results behave differently in simulating the annual rainfall pattern over different ENSO phases (Fig. 22). Similar to results from the three-year average (Fig. 17), the correlation coefficients of RCM results in almost all regions are consistently lower than those of the ERA-Interim data, showing uniform responses throughout the domain. The same goes for RCM RMSE values, which are consistently higher than those of the reanalysis in almost all regions, making them independent of ENSO phase.

Figure 22. Values of the correlation coefficient (top) and RMSE (bottom) based on monthly rainfall of each dataset in different regions over different ENSO phases. Each marker represents different datasets as explained in the legend.

Differently from RMSE and correlation values and, repeating what was seen in the multi-annual mean (Fig. 20), compared to the reanalysis, RCM results show consistent improvement in terms of simulating the seasonal number of rainy days as well as CDD and CWD (Fig. 23). Large improvements are seen in the number of consecutive

wet days, a parameter that tends to be overestimated by ERA-Interim (Kitoh and Arakawa, 1999). This improvement towards precipitation-based derived indices is in agreement with other studies, such as Heikilla *et al.* (2011), who found an improvement in the representation of extreme precipitation events in a 10 km WRF simulation, and Lee and Hong (2014), who concluded that a regional model simulation would increase the skill in simulating both rainfall and temperature indices that are based on day-to-day variability.

Figure 23. Area-averaged biases in climate indices, consisting of dry spells (CDD), wet spells (CWD), and R01 (number of rainy days) for the historical experiments. Each marker represents different datasets according to the legend. Bars and vertical lines crossing the markers are the range of the 95% confidence interval of the corresponding data point.

In order to verify the robustness of the analyses, seasonal rainfall biases are recalculated using the second source of gridded observational values. The selected set comes from the TRMM 3B43 multi-satellite precipitation product with a spatial resolution of 0.25° , lower than CHIRPS' (Huffman et al., 2007). While bias magnitudes differ, their spatial patterns and the relative performance of each scheme are very similar to those identified by the comparison to CHIRPS (Figs. 24 and 25). The KF and GF schemes still show large overestimation with the NSAS parameterization resulting in moderate overestimation and the best performance obtained by the BMJ cumulus scheme. One difference is that in the TRMM 3B43 comparison only two (DJF and MAM) and not three seasons show RMC BMJ simulation biases statistically different from the reanalysis.

In almost all of the tests described above the BMJ and NSAS schemes produce better representations of precipitation over Indonesia than the KF and GF parameterizations. The Kain-Fritsch (KF) scheme (Kain, 2004) is a mass-flux type scheme that preserves clouds over the convective time scale until at least 90% of the Convective Available Potential Energy (CAPE) is removed. It accounts for a variety of processes such as updraft, downdraft, entrainment, detrainment, and tracks multiple water phases including, vapor, water, ice, and snow. Some studies found that the scheme performed well in the mid-latitude over areas where convection is mainly controlled by the movement largescale air masses (Salathe *et al.*, 2010; Bukovsky and Karoly, 2011). However, this is not the case with the maritime continent area, where the atmosphere is

mostly in the state of constant instability and pressure gradients between air masses pressure are not significant. As a result, the RCM output using this KF scheme overestimates rainfall, especially over land. A similar behavior is seen in results generated by Grell-Freitas (GF) scheme (Grell and Freitas, 2011) which uses the same mass-flux algorithm employing explicit cloud processes. However, the GF scheme offers some multiple-closure options in case specific tuning is required.

The New Simplified Arakawa-Schubert (NSAS) scheme (Han and Pan 2011) is a quasi-equilibrium type scheme, a category of convective closure proposed by Arakawa and Schubert to inhibit the intensity of the convective activity, based on the assumption that convective and non-convective processes are nearly balanced. It also explicitly accounts for the cloud process of downdrafts and environmental mass-flux. RCM results using this scheme produce a moderate overestimation. The Betts-Miller-Janjic (BMJ) scheme (Janjic, 1994), on the other hand, is an adjustment-type scheme, in which temperature and humidity profiles are adjusted towards a thermodynamic reference, and precipitation is simply calculated as a result of water vapor conservation. It does not employ explicit cloud processes so that there is no downdrafts and cloud detrainment involved. Furthermore, it utilizes a cloud efficiency coefficient that modifies the post convective profile, allowing less saturation to occur. Due to these features, the BMJ scheme generates less rainfall than the other three cumulus parameterizations tested here. However, BMJ results underestimate the amount of rainfall over the low land area (explained next).

Seasonal Rainfall Bias - ERA-Interim - 3-Y. Ave. (TRMM)

Figure 24. Biases of seasonal rainfall for the historical experiments. The first row shows the difference of the ERA-Interim reanalysis with the TRMM 3B43 observation data. Second to the fifth row shows the difference of the RCM results with the TRMM 3B43 observation data, with different schemes for each row, consisting of the KF, BMJ, GF, and NSAS respectively. Units shown are in percent.

Figure 25. Area-averaged value of the biases in seasonal rainfall against the TRMM 3B43 data. Each marker represents different datasets according to the legend. Bars and vertical lines crossing the markers are the range of the 95% confidence interval of the corresponding data point.

So far, in terms of representing seasonal rainfall, the BMJ parameterization shows the highest skill compared to the other tested schemes and it even provides some improvement in the relationship to the reanalysis as shown by the reduced biases in some seasons. In addition, all RCM results show larger skill in simulating some rainfall indices related to the frequency of rainy days. However, RCM results fail to reproduce a relevant annual rainfall pattern for the whole domain area as well as its sub-regions, be it in the

multiannual mean or during different ENSO phases. RCM experiments also produce high RMSE values and lower field correlation values.

A possible cause for this shortcoming is the RCM oversensitivity to topography, resulting in extreme occurrences of orographic rainfall over mountainous areas. Fig. 26 shows a comparison of average seasonal rainfall during 2013, the ENSO neutral year. It is clear that the BMJ RCM overestimates precipitation over regions with high elevation and underestimates rainfall over lowland and coastal areas. ERA-Interim produces more homogeneously distributed precipitation, closer to the patterns seen in TRMM and CHIRPS observations. This difference in spatial distribution is, perhaps, causing an erroneous representation of rainfall evolution over the year as explained before. A possible way to overcome this problem is by using a nested domain within the RCM with higher spatial resolution, as previously demonstrated in Lee and Hong (2014), who found that the error in spatial distribution of precipitation and temperature are reduced in simulations using a secondary nest with a higher resolution (12 km) inside a medium resolution (50 km) domain.

Figure 26. The average seasonal rainfall of the year 2013. Top left is the TRMM 3B43 data. Top right is the CHIRPS data. Bottom left is the ERA-Interim reanalysis. Bottom right is the RCM simulation result using the BMJ cumulus scheme. Units shown are in millimeters.

The RCM lack of skill does not necessarily mean that it failed to simulate the pertinent physical mechanisms determining precipitation. Further investigation is done by comparing BMJ RCM, ERA-Interim and CHIRPS single grid point values of daily rainfall accumulation to values recorded at six ground observation stations within Indonesia. Three of them are located near the coast; Temindung ($117^{\circ} 9' 11''$ E, $0^{\circ} 35' 30''$ S), Cengkareng ($106^{\circ} 40' 48''$ E, $6^{\circ} 7' 24''$ S), and Lombok ($116^{\circ} 31' 59''$ E, $8^{\circ} 40'$ S) with the other three in inland mountainous areas; Sicincin ($100^{\circ} 24'$ E, $0^{\circ} 21'$ S), Citeko (106°

56° 6' E, 6° 41' 52" S), and Darmaga (106° 44' 59" E, 6° 33' 12" S). Results are shown in Fig. 27. It can be seen that, while the RCM overestimates precipitation over mountainous terrain and underestimates it over flat areas, it does a better job at separating the low and high elevation precipitation locations than the reanalysis and gridded observations. These findings suggest a contrast of rainfall amount between different topography settings that was missed by both ERA-Interim and CHIRPS but captured by the RCM.

Figure 27. Running daily rainfall of the year 2013. Top left is the surface observation data. Top right is the CHIRPS data. Bottom left is the ERA-Interim reanalysis. Bottom right is the RCM simulation result using the BMJ cumulus scheme. The legend shows different observation points. Stations located near the coastline are displayed with blurred lines, while stations near mountain area are displayed with opaque lines.

Overall, RCM results are shown to be sensitive to the presence of topography. A possible explanation for this is that the convection processes associated with the diurnal cycle over land and sea within the maritime continent area are not represented correctly. According to Teo *et al.* (2011), RCMs amplify the basic diurnal forcing over land, particularly in regions with rough topography. Collier and Bowman (2004) attributed this type of bias in modeled precipitation to the inability of models to represent phase and amplitude of the diurnal cycle over land appropriately. Fig. 28 provides another example of the overestimation of precipitation over topography, suggesting that the enhanced convection by mechanical lifting due to orography over the mountainous region is exaggerated in the RCM.

Figure 28. Area-averaged values of seasonal rainfall for the historical experiments. Each marker represents different datasets according to the legend. Bars and vertical lines crossing the markers are the range of the 95% confidence interval of the corresponding data point.

4.2 Future projection simulations

The previous section evaluated RCM ability to reproduce rainfall patterns in historical experiments. One cumulus scheme, Betts-Miller-Janjic (BMJ), was found to be distinctively better than others by presenting the lowest biases. This particular convective parameterization setting is adopted in future projection simulations forced by projections from the MPI-ESM-MR GCM. The goal of these future simulations is to provide higher resolution descriptions of possible future changes in precipitation.

As with historical simulations, the daily rainfall value from both the GCM and WRF RCM outputs are organized into seasonal rainfall values. The results are then averaged across multiple years within each respective period. For the Baseline period, three different years representing different ENSO states (2007, 2012, 2014) are averaged into a multiannual mean. A similar procedure is followed for the Near-Future (2036-2040) and Far-Future (2096-2100) periods. The resulting seasonal rainfall values are plotted in Fig. 29.

As in what takes place in relation to the reanalysis in the historical simulations, when compared to GCM output, the RCM generates excessive rainfall over high elevation areas. RCM results also produce more rainfall over the ocean than the GCM, particularly over areas and times in which moisture is abundant: the southeastern part of the maritime continent during DJF and the northern portion of the domain during JJA. Another feature worth noticing is the existence of two high precipitation clusters (one to the north and one to the south) during the transitional seasons (MAM and SON) over the eastern part of the maritime continent. This feature is not related to the overestimation during DJF and JJA (associated with the Indo-Australian monsoon and ITCZ position). It is not present in the GCM and exclusive to RCM results. Overall, RCM performance is relatively consistent over different time periods, suggesting no significant differences in model behavior between different time slices.

Seasonal Rainfall - MPI-ESM-MR - Baseline

Seasonal Rainfall - MPI-ESM-MR - Near Future

Seasonal Rainfall - MPI-ESM-MR - Far Future

Figure 29. Seasonal rainfall for the future projection experiments. The first and the second rows show the Baseline period. The third and the fourth rows show the Near-Future period. The fifth and the sixth rows show the Far-Future period. Units shown are in millimeters.

To determine possible future changes in rainfall, differences between the Baseline and both future periods are calculated as biases in percent. It is clear that RCM results produce similar spatial patterns during both future periods (Fig. 30). Even though there is a different tendency in some areas between the GCM and RCM, the values of the biases are not significantly different.

An increase in the contrast between mean precipitation during wet and dry seasons is seen by many GCM simulations under warming climate conditions (IPCC, 2013). It has also been identified in a 10-year future (2045-2054) simulation using WRF forced by data from a GCM (ECHAM5) simulation conducted under an AR4 A1B emission scenario over Southeast Asia (Chotamonsak *et al.*, 2011). While a pattern of less rainfall during both hot and cold dry seasons and more rainfall during wet seasons is dominant, it is not found in all areas, and opposite trends took place over the eastern coast of Vietnam, southern coast of China, northern coast of Borneo and the Java Sea (Chotamonsak *et al.*, 2011).

My RCM results confirm the potential heterogeneity of the seasonal response to warming, particularly in the Near-Future experiments, where a decrease in precipitation is simulated during the monsoonal (DJF) wet season (Fig. 30). As for the Far-Future period, the southern part of the maritime continent, mainly affected by the Indo-Australian monsoon, displays a clear wetter tendency, while the northern part, which experiences less rainfall at that time of the year, becomes drier during the DJF season (Fig. 30). A reduction in monsoonal dry-season RCM precipitation is seen in both Near-Future and Far-Future experiments. During both of the transitional seasons (MAM and

SON), however, RCM results, as well as the GCM, show an increase of rainfall over most of the domain in both Near-Future Far-Future experiments (Fig. 30).

Figure 30. Changes in future rainfall based on GCM and RCM results presented as biases in seasonal rainfall. The first and the second rows show the future rainfall changes (Near-Future period and Far-Future period, respectively) in the MPI-ESM-MR GCM. The third and the fourth rows show the future rainfall changes (Near-Future period and Far-Future period, respectively) in the RCM results. Units shown are in percent.

The RCM-simulated annual pattern of rainfall over land, expressed as area-averaged monthly precipitation, is shown in Fig. 31. Both future patterns of rainfall show

relatively high similarities with the baseline period (correlation coefficient of 0.82), indicating the continuing dominance of the Indo-Australian monsoon for the whole area. Other than the already noted increase in rainfall during the transitional months of April and November (Fig. 30), there are no significant differences between Baseline and Near Future simulations. The changes in the mean rainfall amount are more significant in the Far-Future period, in agreement with previous studies (IPCC, 2013; Chotamonsak *et al.*, 2013), in which a drier dry season and a wetter wet season are expected. The diagram shows a significant decrease in rainfall during the monsoonal dry season, with mean minimum rainfall below 180 mm in July, and significant increase during the wet season peak with mean maximum rainfall exceeding 340 mm in November. The rainy season peak is shifted and occurs two months earlier (January to November) compared to the Baseline and Near-Future periods (Fig. 31).

Figure 31. Area-averaged value of monthly rainfall for the GCM based experiments.

Each line represents different periods. The differences between each value of those three periods are significant within the 95% confidence level, providing an average confidence interval of ± 2.8 on each data points (not shown in the figure).

Figure 32. Same with Figure 31 but divided into several regions as those in the previous section. The differences between each value of those three periods are significant within the 95% confidence level, providing an average confidence interval of ± 3.3 on each data points (not shown in the figure).

The area-averaged monthly precipitation is also divided into the previously defined areas (Fig. 14) within the domain, with results shown in Fig. 32. Regions dominated by monsoonal type rainfall, such as Java and Lesser Sunda, exhibit relatively fewer changes in annual precipitation pattern. Large landmasses (such as Sumatra, Borneo and New Guinea), which occupy regions with more than one annual rainfall pattern type, show some future alteration to annual patterns while areas with a very heterogeneous distribution of rainfall types, such as Celebes, display the most significant changes in annual rainfall pattern in the future.

The historical experiments described above have demonstrated the added value provided by RCM simulations when it comes to representing the number of rainy days, CDD and CWD indices. Changes to these in future periods are displayed in Fig. 33. Overall, indices follow the tendencies in seasonal rainfall amount displayed in Fig. 30. There is an almost uniform increase in the number of rainy days and CWD as well as a uniform decrease in CDD during the monsoonal wet season. A wetter trend during transitional months is also apparent in all indices, with a significant increase in CWD in particular. An important difference, however, is seen between the Near-Future and Far-Future monsoonal dry season. Near-Future indices suggest wetter conditions in JJA, indicated by significant increase in the number of rainy days and CWD and decrease of CDD, while drier JJA conditions generated by the Far-Future simulation.

Figure 33. Changes in future rainfall indices. The first and the second rows show the future changes of the number of rainy days. The third and the fourth rows show the future changes of consecutive dry days value (CDD). The fifth and the sixth rows show the future changes of consecutive wet days value (CWD). Units shown are in percent.

Another possible risk of drought in the future comes from the changes in soil moisture. The seasonal distribution of soil moisture in each period is displayed in Fig. 34 (top three), along with their future changes (Fig. 35, bottom two). According to simulations, Sumatra is the area most susceptible to drought, with future decreases in soil moisture projected in most of its area for all seasons. Soil moisture also tends to decrease during the monsoonal wet season (DJF) during both future periods, even though the rainfall projection shows an increasing trend during the Far-Future period. In general, the Far-Future period shows a more uniform tendency in reduced soil moisture compared to the Near-Future period. The Far-Future period distribution shows moderate to significant decreases (-2.5 to -10 percent), with some areas experiencing small increases (0 to 2.5 percent). These patterns are in agreement with the changes in soil moisture in the end-of-century period (2081-2100) retrieved from 32 multi-model ensembles with the RCP8.5 scenario documented by the IPCC (2013), which suggests a decrease in soil moisture in the region surrounding the Java Sea as seen in Fig. 34 (bottom).

Figure 34. Soil moisture and its change in the future based on RCM results. The first three rows show the average seasonal (DJF, MAM, JJA, SON – from left to right by column) values in each period (Baseline, Near-Future, and Far-Future period, respectively) from the GCM-forced simulations. The last two rows show the future changes (Near-Future period and Far-Future period, respectively) in the RCM results. Units shown are in percent.

The difference in the changes of rainfall and soil moisture between the Near-Future and Far-Future period might as well be attributed to the difference in the

magnitudes of warming between those two. Fig. 35 shows the spatial distribution of mean near-surface temperature for each period, as well as both future anomalies relative to the Baseline period. As explained in Chapter 2, the variability of temperature in the annual timescale is not significant, leaving no distinct variation of the temperature spatial patterns between seasons. It is also apparent that the difference of the increase in temperature between two future periods is significant, with values ranging from 0°C to 1°C for the Near-Future, and 2°C to 6°C for the Far-Future. Again, these values are in agreement with the multi-model ensemble projected warming from the IPCC report (2013) in both Near-Future and Far-Future period. The temperature rises in the Near-Future are also similar to another RCM-based experiment forced by the ECHAM5 GCM (Chotamonsak *et al.*, 2011) that documented an increase in the range of 0.77 °C and 1.37°C in the near future. The uniform trend of decreasing soil moisture across different seasons in the Far-Future period – despite a different tendency in seasonal rainfall – is most likely associated with the increase evaporation induced by the extreme warming. The multi-model ensemble IPCC report (IPCC, 2013) projected an end of 21st-century increase in evaporation ranging 0.2 to 0.6 mm/day over the maritime continent area with more than 90% agreement from 37 models.

Temperature - MPI-ESM-MR Downscaled

Changes in Future Temperature - MPI-ESM-MR Downscaled

Figure 35. Near-surface temperature and its change in the future based on RCM results.

The first three rows show the average seasonal (DJF, MAM, JJA, SON – from left to right by column) values in each period (Baseline, Near-Future, and Far-Future period, respectively) from the GCM-forced simulations. The last two rows show the future changes (Near-Future period and Far-Future period, respectively) in the RCM results.

Units shown are in degree Celsius.

Chapter 5: Conclusions and Future Work

5.1 Conclusions

A series of regional climate simulations forced by both reanalysis data and future GCM output is conducted with the ultimate objective of providing skillful, high-resolution future rainfall projections over Indonesia.

RCM results from historical experiments forced by the ERA-Interim reanalysis have shown that the increase in spatial resolution provides a more detailed spatial distribution of rainfall, particularly in areas of varying topography. Four different convective parameterizations are compared, with one of them, the Betts-Miller-Janjic scheme, showing larger skill than the other three and the ERA-interim reanalysis in reproducing mean seasonal rainfall.

Nevertheless, even when compared to the best performing RCM configuration, the reanalysis offers a better representation of the annual rainfall pattern based on the time series of monthly rainfall. The most convincing added value provided by the regional simulations is a better representation of three rainfall-related climate indices: consecutive dry days, consecutive wet days and number of rainy days. This improvement is statistically significant and found in all seasons.

Based on the bias of the seasonal rainfall, September-October-November (SON) is the season in which RCM and ERA-Interim show the worst performance, independent

of ENSO phase and, in general, the skill of both reanalysis and RCM decreased under El Niño conditions. RCM response to different phases of ENSO is not uniform between regions inside the domain of study. The tendency in which the RCM provides a better representation of rainfall-related climate indices and worse representation of the average annual rainfall pattern is independent of ENSO phases.

A possible reason for the lower skill in representing the annual rainfall pattern is the RCM's overestimation of orographic precipitation, which results in anomalously high rainfall over mountainous areas and an incorrect representation of the diurnal cycle in convective mechanisms. However, from a comparison with several ground-based observation data, it is shown that RCM results, while overestimating precipitation in general, offer a better representation of the difference between the precipitation regimes over flat terrain and rough topography.

Future RCM simulations experiments forced by the MPI-ESM-MR GCM display a consistent increase of rainfall during transitional seasons (MAM and SON). Nonetheless, different periods in the future displaying different tendencies. The monsoonal wet season (DJF) tends to be drier and the dry season (JJA) wetter in the Near-Future (2036-2040) experiments while the Far-Future (2096-2100) results show the opposite trend. The latter tendency in agreement with previous studies. The annual rainfall pattern from Far-Future simulations shows a 2-month delay (from May to July) in the peak of the wet season. These simulations also point to an increase in the magnitude of wet season rainfall and decrease in the dry season precipitation.

5.2 Future Work

Only three years were analyzed by historical simulations, the assumption being that each represented characteristics under a particular ENSO phase. As the magnitude and spatial patterns of ENSO anomalies differ between events, the impacts of the oscillation would be better evaluated by increasing the number of simulations so that more than a single realization of each phase could be analyzed. As for the future simulations, incorporating multiple GCMs with various emission scenarios and physical realizations in the regional simulations would provide better insight on uncertainties associated with future regional rainfall change over Indonesia. More cumulus physics schemes and other parameterizations, such as microphysics, radiation model, and planetary boundary layer schemes could be analyzed by perturbed physics ensembles as suggested by Ulate *et al.* (2014).

Considering that rainfall in the maritime continent is highly related to local scale convection, and having in mind that Indonesia is an area with complex topography and heterogeneous land surface, it would be intriguing to know whether there would be an improvement in model skill if the regional simulations were done at finer spatial resolution, particularly since improvements related to increased resolution has been recorded for other areas with similar characteristics (Evans *et al.*, 2012; Lee and Hong, 2014; Soares and Cardoso, 2017). Another important step is to investigate the possibility of conducting simulations at a cloud-resolving scales without parameterized convection and see if the results could provide the expected added values.

Future research should consider using a more comprehensive observation dataset as a reference. This study has identified a lack of dependability of satellite-based observation data, especially in differentiating the spatial response associated with differences in topography. There are more than 6000 rainfall observation locations of rainfall over Indonesia with varying data range and quality. These are valuable assets and, quality checks should be considered for inclusion upcoming gridded rainfall products.

Lastly, there are various aspects of analysis that are not covered in this study. The rainfall bias is highly related to simulated moisture flux and convergence, indicated by the tendency in specific humidity and upper and lower level wind components in a horizontal and vertical sense. It is also important to verify the role the temperature plays in influencing humidity, especially in the context of a warming world.

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