Assessing risks of climate variability and climate change for Indonesian rice agriculture

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El Niño events typically lead to delayed rainfall and decreased rice planting in Indonesia's main rice-growing regions, thus prolonging the hungry season and increasing the risk of annual rice deficits. Here we use a risk assessment framework to examine the potential impact of El Niño events and natural variability on rice agriculture in 2050 under conditions of climate change, with a focus on two main rice-producing areas: Java and Bali. We select a 30-day delay in monsoon onset as a threshold beyond which significant impact on the country's rice economy is likely to occur. To project the future probability of monsoon delay and changes in the annual cycle of rainfall, we use output from the Intergovernmental Panel on Climate Change AR4 suite of climate models, forced by increasing greenhouse gases, and scale it to the regional level by using empirical downscaling models. Our results reveal a marked increase in the probability of a 30-day delay in monsoon onset in 2050, as a result of changes in the mean climate, from 9–18% today (depending on the region) to 30–40% at the upper tail of the distribution. Predictions of the annual cycle of precipitation suggest an increase in precipitation later in the crop year (April–June) of ≈10% but a substantial decrease (up to 75% at the tail) in precipitation later in the dry season (July–September). These results indicate a need for adaptation strategies in Indonesian rice agriculture, including increased investments in water storage, drought-tolerant crops, crop diversification, and early warning systems.

empirical downscaling models | risk assessment

Agricultural production in Indonesia is strongly influenced by annual and interannual variations in precipitation, caused by the Austral–Asia monsoon and El Niño–Southern Oscillation (ENSO) dynamics. Indonesia consistently experiences dry climatic conditions and droughts during the warm phase of the ENSO cycle (El Niño), with significant consequences for agricultural output, rural incomes, and staple food prices (1, 2). The year-to-year dynamics of ENSO and precipitation over the archipelago have been well studied (3–6), as have various links between ENSO, crop production, and famines in different parts of the country (7–10). Over the longer run, rising concentrations of greenhouse gases will likely create additional climate impacts on Indonesian agriculture. The combined forces of climate variability and climate change could have a dramatic effect on agricultural production in Indonesia and other tropical countries.

Here, we present a framework for assessing the risks of climate change for Indonesian rice agriculture, drawing on the observational record of interannual variability in precipitation and production and on projections of climate change. We focus on precipitation, rather than temperature, because the links between precipitation and production in Indonesia are significant and well documented. Our earlier work (1) showed that ENSO has been the primary determinant of year-to-year variation in Indonesian rice output over the past three decades, accounting for almost two-thirds of the total variation. During El Niño events, Indonesia's production of rice, the country's primary food staple, is affected in two important ways: (i) delayed rainfall

causes the rice crop to be planted later in the monsoon season, thus extending the "hungry season" (*paceklik*, the season of scarcity) before the main rice harvest; and (ii) delayed planting of the main wet-season crop may not be compensated by increased planting later in the crop year, leaving Indonesia with reduced rice area and a larger than normal annual rice deficit. This pattern highlights the importance of timing, as well as total production of rice, for food security, which is defined here as the availability and access to staple food commodities for all consumers throughout the year.

A key question for our study is whether natural climate variability (including ENSO) will exert a greater impact on Indonesian rice agriculture and food security in 2050 with changes in the mean climate. To answer this question, we compare the present vs. future likelihood of exceeding a seasonal climate threshold, delayed monsoon onset, which has been shown empirically to be important for rice production and food security during El Niño events in recent decades. We also explore how the annual cycle of rainfall over the archipelago is likely to change, in terms of both the total amount of rainfall over the year and the distribution of rainfall throughout the year. Examining potential changes in the annual cycle of precipitation provides insight into future impacts of ENSO on both wet (monsoon)-season and dry-season rice crops and suggests thresholds that are likely to emerge by 2050. Our analysis covers two regions: (i) West and Central Java and (ii) East Java and Bali (Fig. 1). These areas account for ≈55% of the country's total rice production and are thus watched most carefully from a food policy perspective. Agricultural data series for these regions are also longer and more complete than for other provinces in Indonesia, and rainfall–rice relationships on Java and Bali have been well established in our earlier work (1, 2).

Selecting a Threshold. Climate impact studies apply a variety of threshold concepts, including biophysical, behavioral, and user-designed thresholds (11). Each concept indicates a point beyond which the biophysical, socioeconomic, or institutional system in question is significantly affected by, or fundamentally changes in response to, climate change. The selection of meaningful and operational climate thresholds for risk assessment is not a trivial task. For example, without knowing how markets, preferences, and technology will change in the distant future, it is difficult to know how the relative profitability of crops, and hence farmers'

Fig. 1. Regions analyzed, with corresponding monsoon onset and termination dates, as well as percentage of total Indonesian rice production (2004) (white numerals). Onset date is the date past August 1 when accumulated rainfall equals 20 cm, averaged over reporting rainfall stations in the region for the years 1979–2004; termination date is the date on which 90% of that year's rainfall has accumulated.

choice of crops, will be altered by climate change. Similarly, predicting the point at which a biophysical system will be transformed as a result of climate change is difficult without having experienced prior episodes that are similar to the projected climate.

In this analysis, we rely on our earlier studies of ENSO-based variability to select a climate threshold for Indonesian rice agriculture (1, 2). Understanding the seasonality of rainfall and production is key to this process, because rice plantings follow the rains in the "run-of-the-river" irrigated systems and rain-fed systems that are typical on Java and Bali. Fig. 1 illustrates the regional pattern in monsoon movement, with onset beginning in the northwest, progressing toward the southeast, and terminating initially in the east. The peak of the wet season typically occurs in December–January when the northwest monsoon (which extends from the western Indian Ocean to the date line) sweeps across Java and Bali toward Australia (5, 12). The largest absolute variation in rainfall occurs at the end of the dry season during monsoon onset (September–November) (5).

In neutral ENSO years, the main wet-season rice crop in Java is planted between late October and early December, when there is sufficient moisture to prepare the land for cultivation and to facilitate the early rooting of transplanted seedlings. The main planting season occurs before the peak of the winter monsoon (December–January) because excessive water at the vegetative growth stage hampers rooting and decreases tiller production (13). During the 90- to 120-day grow-out period from transplanting to harvest, ≈20 cm of cumulative rainfall is needed to moisten the ground sufficiently for planting, and ≈100 cm of rainfall is needed throughout the season for cultivation (14). A smaller dry-season planting takes place in April–May after the wet-season crop is harvested.

Unfortunately, this pattern can be disrupted by variations in climate, as in El Niño years. El Niño events cause a delay in monsoon onset by as much as 2 months, postponing the main rice harvest and often driving up prices in domestic and international markets, with a disproportionate impact on poor net consumers of rice (2). Given the observed consequences of a monsoon delay for the Indonesian rice economy in El Niño years, we select a

30-day delay in monsoon onset as the critical threshold for our risk assessment. "Onset" is defined as the number of days after August 1 when cumulative rainfall reaches 20 cm, and "delay" is defined as the number of days past the mean onset date (averaged over the period 1979–2004). Statistical analysis of the observational record shows a correlation between onset delay and total rainfall in September–December (when the main rice crop is planted) of −0.94 for West/Central Java and −0.95 for East Java/Bali, indicating that delayed monsoon onset is associated strongly with decreased total rainfall in this period.

For the period in which rice production data are available for Java and Bali (1983–2004), the probability of a 30-day delay in monsoon onset was 18.2% for West/Central Java and 9.1% for East Java/Bali [see supporting information (SI) Fig. 4]. Although the probability of a 30-day monsoon delay was lower in East Java/Bali than in West/Central Java, the impacts on rice production were higher. A 30-day delay caused rice production to fall by 11%, on average, in East Java/Bali during the main rice harvest season between January and April, as compared with 6.5% in West/Central Java. When we apply these percentage declines to average production for the two regions, we find a comparable drop in rice output of ≈580,000 metric tons in West/Central Java and 540,000 metric tons in East Java/Bali in the January–April period. [Average production in this season was ≈9 million metric tons (mmt) in West/Central Java and 5 mmt in East Java/Bali.] Production declines of these magnitudes, when scaled up to the country as a whole, are at the upper end of what is typically experienced during major El Niño events, such as in 1997/1998 when Indonesia imported 5.8 mmt of rice: 20% of the total world rice trade that year (15).

From the observational record, there is only a weak empirical basis for linking variation in late-season rainfall to dry-season crop production. Econometric analysis shows that a 20% drop in rainfall in April–June reduces the corresponding planting area for Java and Bali by only 2%. Currently, little rice is planted in the subsequent dry season from July to September, but late-season planting patterns could change if precipitation during this period increases or decreases significantly in the future.

If climate change alters the annual cycle of precipitation over

the archipelago, it may be necessary to reexamine the relevance of our current monsoon delay threshold and to explore new thresholds that have not yet been evident in Indonesian rice agriculture. Global climate models (GCMs, also referred to as general circulation models) generally predict warmer and moister atmospheric conditions in the global tropics, because of increased greenhouse gas concentrations, but show much less agreement with respect to the regional and seasonal distribution of rainfall in the tropics (16, 17). Furthermore, the Indonesian archipelago is situated in an especially sensitive region, given that the annual cycle of precipitation will likely be influenced by changes in both the mean temperature and the large-scale dynamical circulation in the tropics. (Indonesia sits under an ascending, and hence rainy, branch of the tropical Walker circulation.) Will warmer atmospheric conditions cause precipitation over the entire annual cycle to increase, or will changes in the dynamical circulation inhibit precipitation in the future? Will precipitation changes be distributed uniformly over the annual cycle or concentrated more tightly around the monsoon, leading to a wetter wet season and a drier dry season? Answers to these hypothetical questions are important for gauging future impacts on both wet- and dry-season rice crops.

Projecting Future Precipitation. Our goal is to understand how the probability of exceeding our climate threshold will change between now and 2050. We use GCMs from the Intergovernmental Panel on Climate Change AR4 report to represent a range of plausible climate scenarios for 2050. Our approach follows the bottom-up approach described by Hulme and Brown (18), in which the focus is on the vulnerability of Indonesia's rice agriculture given a wide range of potential climate outcomes, rather than on a specific climate forecast. Projections of large-scale atmospheric fields (e.g., winds, sea-level pressure, humidity) that feed the annual cycle (monsoon) in Indonesia's climate are available from some 20 different GCMs (the number varies depending on which circulation fields and emissions scenarios are selected) through the Coupled Model Intercomparison Project (19, 20). Although these GCMs simulate the large-scale atmospheric circulation relatively well, the regional hydrological cycle is often poorly reproduced (see SI Fig. 5). Moreover, the coarse grid sizes (typically 200×200 km^2) of GCMs do not resolve the regional-scale (e.g., 50×50 km^2) interactions between the large-scale atmospheric circulation and the very complex and mountainous topography of the archipelago; these interactions are important contributors to the hydrological cycle over Indonesia. The islands of Java and Bali are not even represented as land in many GCMs.

As a result of these constraints, we developed empirical downscaling models (EDMs) that map the observed large-scale circulation patterns and humidity distributions to the observed regional-scale precipitation for Indonesia over the past 50 years (i.e., the EDMs are developed solely on the basis of observations, without reference to the GCMs). The EDMs are then fed into the present-day, large-scale circulation simulated by each GCM to obtain an estimate of regional, present-day precipitation. Hence, to the extent that the models reproduce the observed large-scale circulation with fidelity, the EDMs also act to debias regional precipitation estimates. We find that all of the EDMs do an excellent job of simulating the observed regional precipitation, which indicates that the large-scale circulation is reliably simulated by each of the GCMs (SI Fig. 5). We then apply the EDMs to projected changes in the large-scale circulation forced by increasing greenhouse gas concentrations to produce estimates of future precipitation changes in 2050. Precipitation variations (including those caused by ENSO) derived from the historical record are superimposed on the annual cycle of precipitation in these model projections. EDMs serve as a useful tool for projecting regional climate by using output from GCMs,

for cases in which (*i*) there is a robust relationship between local subgrid-scale precipitation and large-scale atmospheric variables that are simulated reliably by the GCMs, (*ii*) topographical features potentially play an important role in spatial distributions of precipitation, and (*iii*) the observational records are of sufficient duration and quality to determine accurate empirical relationships (21). Indonesia satisfies these minimal criteria.

Capturing uncertainty is a key element in risk assessment. Long-run climate projections entail uncertainty in future emissions of greenhouse gases and aerosols; in climate sensitivity to these emissions; and in regional climate responses to changes in atmospheric and ocean conditions (11). In our framework, we use three EDMs, each of which attributes reasonable but different physically based weights to large-scale circulation variables (see *Data and Methods*), to estimate regional precipitation. We then apply these EDMs to GCMs in the Intergovernmental Panel on Climate Change AR4 report, using the "market-driven growth" (A2) and "environmentally sustainable growth" (B1) scenarios defined in the Special Report on Emissions Scenarios (22). We chose these two scenarios because they represent a realistic range of future emissions and they have been run by a large number of GCMs. We assume that all EDMs and GCMs are equally likely; that is, they all receive the same weight in our assessment of model results for each emissions scenario. This approach enables us to build a probability distribution of possible future outcomes for the annual cycle of precipitation over West/Central Java and East Java/Bali for 2050. From this distribution, we can determine the likelihood of exceeding climate thresholds for rice agriculture (see *Data and Methods*). Use of multimodel ensembles in probabilistic climate projections has been accepted broadly by the Intergovernmental Panel on Climate Change (20, 23).

Results and Discussion

With ENSO variability superimposed on the projected annual cycle of precipitation for 2050, the likelihood of exceeding the 30-day monsoon onset delay threshold increases significantly relative to the current period. Fig. 2 shows the probability distributions of exceeding the threshold in 2050 by region, EDM, and emissions scenario. Each distribution reflects the combined output from 15 to 20 GCMs that have been downscaled to the regional level for Java and Bali. In most cases, with the exception of EDM3 in West/Central Java, the mean likelihood of exceeding the threshold in 2050 is higher than it is today. More importantly, the distribution indicates a substantially greater likelihood of exceeding the threshold for many models included in our analysis. With the A2 scenario for the West/Central Java region as an example, one third of the GCMs downscaled with EDM1 show that the probability of threshold exceedance in 2050 ranges from 23% to almost 33%: notably higher than the current probability of 18.2%. The results are even more striking for the East Java/Bali region. For the A2 scenario, all models project an increase in the probability of threshold exceedance above the current level of 9.1%. One-third of the GCMs downscaled with EDM1 demonstrate a probability of threshold exceedance in 2050 ranging from 19.8% to 40%. Although the probability distributions for both regions and emissions scenarios generally show a greater likelihood of exceeding the monsoon onset delay threshold in 2050, some models show a reduced probability of threshold exceedance.

The results in Fig. 2 provide insight into the nature of uncertainty in the model projections. Uncertainty in the future path of greenhouse gas emissions and their impact caused by climate forcing, as illustrated by the differences between the A2 and B1 scenarios, is relatively insignificant. Less than half a century (2050) is too soon to see the broad climate effects of alternative technology and management approaches (20). On the other hand, uncertainty in the response of large-scale circulation
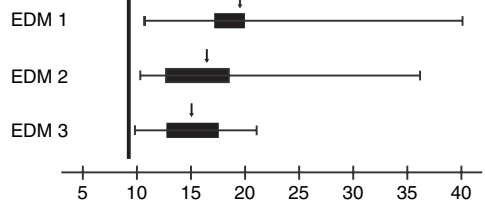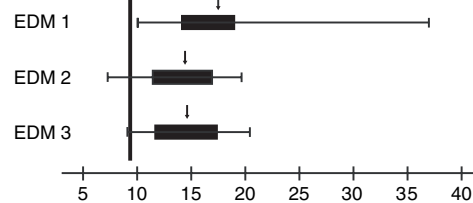
West Java/Central Java – A2 Scenario
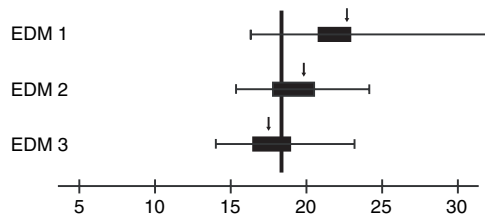
West Java/Central Java – B1 Scenario
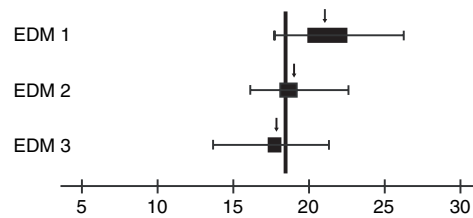
East Java/Bali – A2 Scenario

East Java/Bali – B1 Scenario

Fig. 2. Likelihood of exceeding the 30-day monsoon threshold in 2050 for the three EDMs applied to all GCMs for each scenario (see *Data and Methods*). The probability distributions are divided into terciles, each containing output from one-third of the GCMs with the lowest, middle, and highest projections, respectively. The thick rectangle shows the middle tercile, and the horizontal lines on either side show the lower and upper terciles. Fifteen GCMs ran the A2 scenario (5 models included in each tercile), and 19 GCMs ran the B1 scenario (6–7–6 models in each tercile). The arrows indicate the mean future probability for all GCMs. The vertical lines show the observed probability for 1983–2004.

fields to increased concentrations of greenhouse gases, and the effect of this response on regional precipitation, are important. The wide range of results among GCMs for a given EDM, and among EDMs, illustrates this uncertainty. Even with these areas of uncertainty, however, the bottom line is clear. A 30-day delay in monsoon onset, with all of its ramifications for Indonesian rice agriculture and food security, is very likely to occur more frequently in 2050 than it does today.

Thresholds on the Horizon. Given that most models project an increasing likelihood of a delayed monsoon onset that exceeds the threshold for significant impact on rice production, the question then becomes: How is the annual cycle in precipitation expected to change in response to climate change? If more rain arrived later in the season, and lasted well into the dry season, then perhaps the delay in monsoon onset in September–November would not pose a significant risk to Indonesian rice agriculture and food security. Alternatively, if less rain fell late in crop season (July–August), it is quite possible that the soil would be drier on August 1, causing our climate threshold to be exceeded more frequently in the future.

Our results indicate that projected changes in the amplitude of the seasonal cycle are more pronounced than projected changes in the timing of rainfall (SI Fig. 5); as a result, our existing threshold remains relevant, if not conservative, in 2050. Fig. 3 shows the predicted change in total rainfall over Java and Bali for the periods April–May–June (AMJ, when dry-season planting typically occurs) and July–August–September (JAS, the later period of the dry season when little rice is currently planted) for the A2 scenario. We chose to analyze only one scenario because the difference between A2 and B1 in model projections is not substantial until after 2050, as discussed above. The combination of all GCMs and EDMs used in our analysis presents a clear picture: total rainfall is expected to increase in AMJ relative to the current pattern, but decrease in JAS. In AMJ, total rainfall is projected to increase by ≈10% in the study regions. In JAS, however, nearly all models project a decline in rainfall. Total rainfall is projected to decline by 10–25% on average and by as much as 50% in West/Central Java and 75% in East Java/Bali at the tail end of the distributions. In East Java/Bali, some models

project that total rainfall will drop close to zero for the JAS season.

Three conclusions can be drawn from these results. First, the expected increase in AMJ rainfall would not compensate for reduced rainfall later in the crop year, particularly if water storage for agriculture was inadequate. Second, the extraordinarily dry conditions in JAS could preclude the planting of rice and all other crops without irrigation during these months by 2050. Finally, with reduced rainfall in JAS, the starting point for measuring monsoon onset (August 1) will likely be even drier in the future, suggesting that our monsoon delay threshold could become quite conservative for measuring the impact of climate variability in 2050. An additional threshold of dry-season total

West/Central Java

East Java/Bali
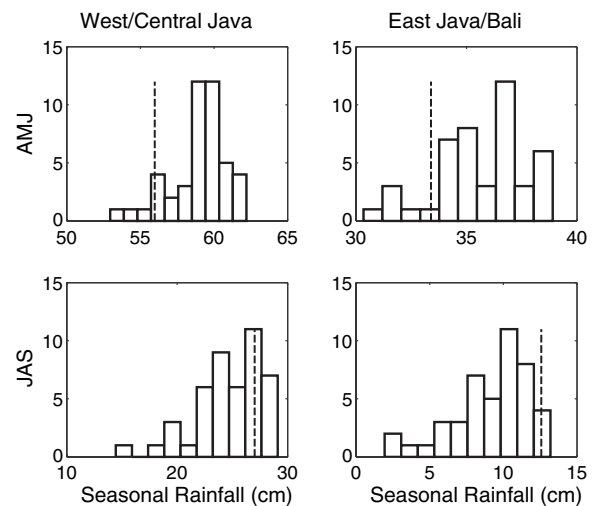
Fig. 3. Summed precipitation for April–June (AMJ) and July–September (JAS) for the present climate (dashed line) and for the future predicted climate, using the A2 scenario. The projected climates are shown as a probability distribution function in which 15 climate models have been downscaled by using the three EDMs (for a total of 45 estimates).

rainfall might, therefore, become important for future climate impact studies of Indonesian agriculture.

Our study focuses on changes in precipitation over Java and Bali and should be considered as a starting point for assessing risks of climate change in regard to rice and other agricultural systems in Indonesia. Increased temperatures and CO_2 concentrations also will affect rice yields in 2050. Results from experimental rice plots at the International Rice Research Institute in the Philippines suggest that rice yields are closely linked to mean minimum temperatures during the dry season; for every 1°C increase in the minimum temperature, rice yields decrease by 10% (24). At a global scale, increased CO_2 concentrations could partially offset expected yield declines caused by lower soil moisture and higher temperature, but recent models suggest a significantly smaller fertilization effect from CO_2 than previously predicted (25). Global models that combine precipitation, temperature, and CO_2 effects for the A2 scenario generally show reduced yields in the tropics and increased yields in temperate zones (26). Further research and modeling of all of these variables could uncover additional climate thresholds that could be used in analyzing risks of climate change in regard to tropical agriculture in the future.

Adaptation. For food-security purposes, several adaptation measures deserve careful consideration, based on the results shown above. First, the development of a rice policy that relies on imports and stock adjustments will become increasingly important in the future for bridging more frequent wet-season delays in rice plantings and harvests and thus for keeping rice prices low for poor consumers. Second, the development of water storage and irrigation infrastructure will be important for balancing increased rainfall in AMJ with decreased rainfall in JAS. Greater storage capacity could help extend the rice production cycle into the JAS period and thus alleviate pressure on poor consumers later in the year. Investing in drought-tolerant rice varieties is another option for securing rice availability and enhancing agricultural incomes and access in dry periods. Finally, a strategy of crop diversification for Java and Bali that focuses on crops suitable for the expected alterations in the annual cycle of rainfall, and that is also responsive to changes in consumer demand with increased urbanization, incomes, and retail chain distribution, should be a priority for food policy planners in Indonesia.

Data and Methods

Calculating Threshold Variables. Our risk assessment model was developed by (*i*) identifying a climate variable with clear effects on rice productivity in Java and Bali, based on the observational record; (*ii*) selecting a threshold for this variable beyond which the loss in productivity was significant; and (*iii*) determining the probability of exceeding this threshold under current and future (2050) climate conditions. Selection of the appropriate climate variable and threshold was facilitated by Indonesia's long experience with ENSO events and our earlier analysis of ENSO-based rainfall variability, rice production, and food security in Indonesia (1, 2). To identify specific threshold indicators for this study, we used least-squares regression models that relate crop production variables (i.e., yield, area, total production by season, and timing of planting and harvest) to observed precipitation for 1979 to 2004. Rice planting and harvesting data for West, Central, and East Java and Bali were available from the Central Bureau of Statistics in Indonesia (27) on a trimester basis (January–April, May–August, September–December). Rice production data were available from 1982/1983 to 2003/2004. Calendar year data were retabulated on a September–August crop-year basis for our analysis.

The precipitation variables were derived from daily rainfall data collected at regional rainfall stations throughout Java and

Bali and reported in the National Oceanic and Atmospheric Administration Climate Prediction Center's Global Summary of the Day archive (28). For each province, we took simple averages of reported values for all stations on a given day to obtain daily average rainfall. Monsoon onset was defined as the number of days past August 1 when accumulated rainfall equals 20 cm: the amount of moisture needed for crop establishment (14). August was chosen as the start date because it is typically the driest month across the archipelago. The effect of onset delay was determined by least-squares regression of detrended rice production for a given trimester as a quadratic function of the monsoon delay (SI Fig. 4). The coefficient on the onset variable reflects the effect on production of delaying onset by 1 day (relative to the average onset date). To obtain the percentage effect on production of a 30-day onset delay, we multiplied the coefficient by 30 and divided the total by the average production for the region over the entire period. The statistical analysis was conducted using the Stata 9 statistical package (StataCorp, College Station, TX).

Developing the EDMs. The GCMs used to project the impact of increasing greenhouse gases on climate are fraught with biases and have a spatial resolution that is too crude to simulate regional precipitation in Indonesia. Therefore, we constructed EDMs to project future patterns of precipitation over Java and Bali for 2050. The EDMs were constructed by applying maximum covariance analysis to the (predictor) annual cycle of observed large-scale circulation fields and the (predictand) annual cycle of observed regional precipitation. The predictor comprises the monthly averaged circulation variables spanning 60°E to 80°W, 30°S to 30°N; the predictand is the monthly averaged rainfall for all 24 provinces in Indonesia. In using the EDM/GCM models to estimate the annual cycle in precipitation over Indonesia in 2050, we are assuming that changes in the large-scale circulation and humidity fields due to increasing greenhouse gases strongly project onto three predictor modes that currently account for the dominant annual cycle in observed regional precipitation. The predictor fields are sea-level pressure, the 850-mb and 200-mb zonal winds, and the specific humidity at 850 mb. The first three fields define the large-scale winds at their respective levels in the troposphere and are typically used to reflect the monsoon circulations. Humidity was chosen because it is related to the overall strength of the hydrologic cycle in the tropics, which is expected to change with increasing greenhouse gases. We have no *a priori* way to judge which combination of humidity and circulation fields will best capture the changes in regional precipitation due to increased greenhouse gases. As a result, we constructed three EDMs, using various combinations of the observed large-scale fields as predictors:

- *EDM1 (850-mb specific humidity)*. This variable represents possible changes in the hydrological cycle that arise as a result of mean warming; a warmer climate is expected to have a more vigorous hydrological cycle because of the expected increase in humidity in the atmosphere. However, specific humidity may not adequately capture changes in dynamical processes, such as changes to the Walker circulation.

- *EDM2 (850-mb specific humidity and sea-level pressure)*. Sea-level pressure variations are strongly related to the dynamical circulation in the tropics (e.g., ENSO and the Walker circulation) and the seasonal cycle, but alone this variable may not capture the mean moistening of the atmosphere that is expected with warmer temperatures. We therefore combined the physical process of sea-level pressure with the hydrologic process of humidity generated by warming.

- *EDM3 [850-mb specific humidity, upper (200-mb)- and lower (850-mb)-level zonal winds]*. Zonal winds represent the monsoon shear line (29) and therefore correspond very strongly to variations in monsoon onset date. As the monsoon sets in, the

surface winds shift from easterly to westerly, and winds aloft shift from westerly to easterly. Thus, upper- and lower-level winds may capture changes in monsoon onset and retreat. Again, because this field does not adequately capture the hydrological cycle, we added 850-mb specific humidity.

For EDM2 or EDM3, we weighted the effects of dynamical processes and hydrological processes equally. If future hydrological processes are more important, and there is no change in the dynamical processes (monsoon and ENSO), then the signal from the hydrological processes may be slightly muted by these two EDMs.

For all three EDMs, the predictor modes captured the annual cycle of regional precipitation for most of the provinces in Indonesia remarkably well and were especially skillful for Java and Bali. SI Fig. 5 shows the raw and reconstructed annual cycle of precipitation for West/Central Java for the present-day AR4 simulations, as well as the projected annual cycle of precipitation for the Special Report on Emissions Scenarios A2 and B1. The figure demonstrates that the EDMs are an effective means of removing the very large bias in simulated precipitation over Java.

The large-scale predictor data were taken from the reanalysis project of the National Center for Environmental Prediction and the National Center for Atmospheric Research (30). The observed climatologically and provincially averaged precipitation was taken from the University of Delaware's Climatologically Aided Interpolation (31), which is a 50 × 50-km grid precipitation product. These data are available for 1950–1999, which covered a sufficient period of time to determine the skill of the EDM. We compared this precipitation product with a station-based precipitation product used in the threshold analysis and found excellent agreement over the seasons of interest for this study (e.g., average correlations between the two sets were 0.90 for May–November and 0.96 for August–October, the key period of monsoon onset).

To simulate the climatological annual cycle in regional rainfall in 2050, we fed the output from the AR4 GCM large-scale fields for the period 2000–2050 into each EDM to obtain the downscaled regional precipitation. The time series for each individual month (e.g., January 2001, January 2002, . . ., January 2050) showed a nearly linear trend in precipitation. As a result, we linearly interpolated the downscaled precipitation for each calendar month to obtain the annual cycle in regional precipitation for 2050. Finally, for each month, we linearly interpolated from monthly to daily resolution to obtain the new climatological onset day.

To estimate the natural variability in onset date, we assumed that the natural (unforced) variability in precipitation is invariant in time and is well represented by the observed 1950–2000 anomalies about the observed (1950–2000) climatological annual cycle. In principle, the EDMs can also be used to simulate the change in natural variability associated with this climatological mean state; although the EDMs were developed by using the climatological annual cycle, when fed the observed anomalies in the large-scale fields they also do a fairly good job of simulating the observed rainfall anomalies. Unfortunately, only one of the AR4 models used to project future climate has realistic ENSO variability. Because ENSO is responsible for nearly half the variance in the precipitation in Indonesia, applying the EDMs to the output of the AR4 models would thus grossly underrepresent the natural variability in Indonesia precipitation, both in today's climate and in the future climate. To sidestep this problem, we made a first-order assumption in this study that the natural variability is invariant in time. Hence, the cumulative probability distribution for precipitation in 2050 was constructed by adding the observed (1950–2000) regional precipitation anomalies to the 2050 climatological mean precipitation.

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