

Draft: July 20, 2009

Final Report  
July 20, 2009

**“Agricultural Decision-Making in Indonesia with ENSO Variability: Integrating Climate Science, Risk Assessment, and Policy Analysis”**

PIs: Rosamond Naylor, Stanford University  
David Battisti, University of Washington  
Daniel Vimont, University of Wisconsin  
Walter Falcon, Stanford University

Award ID: 0433679

Project start date: 10/02/04

**Project summary**

Agricultural production in Indonesia is strongly influenced by the annual cycle of precipitation and the year-to-year variations in the annual cycle of precipitation caused by El Niño-Southern Oscillation (ENSO) dynamics. The combined forces of ENSO and global warming are likely to have dramatic, and currently unforeseen, effects on agriculture production and food security in Indonesia and other tropical countries. This project combined general circulation model (GCM) experiments and empirical downscaling models (EDMs) to assess the influence of global warming on the annual cycle, and on ENSO-induced changes in precipitation and agricultural production in Indonesia. A risk assessment framework was then developed to evaluate how climate-related uncertainty and probable agricultural outcomes derived from the downscaling model can be used in policy decision-making processes. The models focused on rice, the country's primary food staple.

The influence of global climate change and variability on regional-scale processes (especially precipitation) was assessed via the development of EDMs and new GCM simulations. The EDMs used standard statistical techniques to relate features of the large-scale atmospheric circulation (typically well simulated by GCMs) to regional hydrology (not well simulated by GCMs, but with known relationships to the large-scale circulation). The project first developed and cross-validated the EDMs using observed regional precipitation over the past 50 years, as well as observed and GCM-simulated large-scale climate variables like winds and moisture distribution. These EDMs were then applied to a few GCM-simulated climate scenarios (A1, B2) that include increased greenhouse gas forcing and historical patterns of ENSO variability, resulting in a set of regional climate scenarios for Indonesia in the mid-21st century. A model was developed to gauge how the annual cycle of precipitation is likely to change in Indonesian rice growing regions with global warming.

A regression model was used to estimate rice production (area, yield, and total production) as a function of sea surface temperature anomalies (Niño 3.4 SSTAs) and

precipitation across different regions in Indonesia holding technology, markets, and policy constant. A risk assessment framework was employed to link expected changes in SSTAs to the timing of monsoon onset and rice output during the “season of scarcity” (*paceklik*) in 2050. The risk framework focused specifically on the likelihood of critical threshold exceedance, which we defined as a 30-day delay in the onset of the monsoon.

Briefly, our results showed 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 in 2050. These results indicated the urgent need for adaptation strategies to deal with these new climate forecasts.

Further work has sought to deepen our understanding of how the variability of climate itself might change as the mean state changes. In initial work, we assumed that the variability in precipitation over Indonesia due to ENSO in future climates was the same as in the present climate. This was a necessary assumption because only two of the twenty-three AR4 GCM models used to project the future climate have plausible representations of the ENSO phenomenon. Progress in this aspect of the project, still ongoing, is detailed below.

Key project results have been presented to the Agricultural University in Bogor Indonesia, the Ministry of Agriculture, and the Indonesian Department of Meteorology. The work received quite a bit of attention in Indonesia, and was reported on the front page of the *Jakarta Post* when it was first released. The work has also been presented at seminars around the U.S., and has led to numerous subsequent research activities, also detailed below.

## **Project activities and findings**

### ***1. Development of Indonesian climate change scenarios through downscaling models***

One primary goal of the project was to construct plausible scenarios for changes in regional precipitation and other relevant climate variables (over Indonesia under conditions of global warming. Annual and interannual variations in Indonesian precipitation are largely determined by the annual march of the monsoon and by ENSO variations, both of which involve changes in the large-scale atmospheric circulation. While the atmospheric response to these large-scale circulations is relatively well simulated by GCMs, the large-scale hydrological cycle is often poorly reproduced. On regional scales (e.g., 50x50 km<sup>2</sup>) the hydrological cycle in Indonesia is in part determined by interactions between the large-scale circulations and the very complex and mountainous topography of Indonesia. Unfortunately, the coarse grid sizes (typically 200x200 km<sup>2</sup>) of GCMs used to project climate change due to greenhouse gas increases do not resolve small scale, large amplitude topographic features. Indeed, the whole island of Java is often left out of these climate models.

Thus developing plausible climate change scenarios for Indonesia required developing

empirical downscaling models (EDMs) to relate the large-scale circulation patterns and moisture distribution from atmospheric GCMs to the observed regional precipitation over the past 50 years. These EDMs work when (i) there is a robust relationship between local sub-grid scale precipitation and large-scale atmospheric variables that are resolved by a GCM, (ii) when there is complex topography, and (iii) when the observational records are of sufficient duration and quality to determine accurate empirical relationships – criteria all satisfied in the Indonesia case.

A major focus of this project was the development and assessment of the EDMs, which required an estimate of actual precipitation on a provincial scale in Indonesia, and an ability to relate variations in precipitation to large-scale climatic variables. We developed two sets of regional precipitation inventories over Indonesia: an inventory based on interpolated, gridded data, and a station-based inventory. The former (from the gridded data) was more straightforward, but suffered from inhomogeneous data records. The latter (the station-based inventory) required evaluating (often individually) and combining station records of precipitation from 729 stations into a homogeneous data set. The resulting two station inventories provided two separate, and often differing, estimates of provincial scale precipitation.

The Edams were then constructed and tested over the observed record. We tested seven different EDM methodologies using six different sets of large-scale variables. Results indicated that downscaling using modeled large-scale precipitation (a technique that has been demonstratively useful outside of the tropics) would not work for Indonesia due to large biases in modeled precipitation. In contrast, our proposed methodology of using large-scale variables of relevance to hydrological variability in Indonesia provided a better estimate of the seasonal cycle and interannual variability over the region. Based on our validation of the EDMs over the observed record, we chose to use three different EDMs to debias and downscale output from the global climate models.

Figure 1 shows our success in downscaling GCM output to match observed precipitation patterns in Indonesia. The left panel, which is the raw GCM output, shows the substantial biases of nearly all models in reproducing precipitation climatology over Java. The right panel, which downscales this output using one of our three EDMs, demonstrates how well these EDMs perform in de-biasing the GCM output.

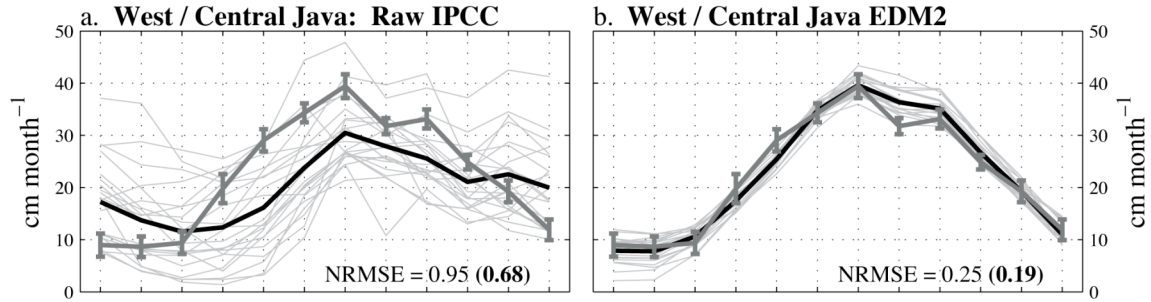


Figure 1. Annual cycle of precipitation over West/Central Java (in cm per month). (a) Raw observed precipitation with 2s errors on the mean (thick gray line with error bars) plotted together with the raw precipitation output from each of the viable models contributing to the AR4 model simulations (thin gray lines) and the ensemble mean from those models (solid black line). This graph demonstrates the very large bias in the model simulations prior to downscaling. (b) As in a, but model output is downscaled using EDM2 (i.e., precipitation is reconstructed using large-scale 850-mb specific humidity and sea-level pressure). Also shown in a and b are the root mean square error averaged over all of the model simulations, as well as the root mean square error of the ensemble mean estimate (in parentheses), both normalized by the standard deviation of the observed annual cycle. Graph b demonstrates the drastic improvement in bias after applying the EDM, which allows the EDM model output to be used in calculating monsoon onset thresholds.

Because EDMs were constructed using relationships between large-scale fields and local precipitation outcomes, and because we had no a priori reason to prefer one set of large-scale fields as predictors over another, we constructed three different EDMs with which to project future climate:

1. *EDM1: 850mb specific humidity.* We chose this variable to represent possible changes in the hydrological cycle that arise due to mean warming. In particular, a warmer climate is expected to have a more vigorous hydrological cycle due to the expected increase in humidity in the atmosphere (warmer air can hold more water than colder air). However, specific humidity may not adequately capture changes in dynamical processes, such as changes to the Walker circulation.
2. *EDM2: 850mb 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.
3. *EDM3: 850mb specific humidity, upper (200mb) and lower (850mb) level zonal winds.* Zonal winds were chosen because they represent the monsoonal shear line (31) 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 850mb specific humidity.

To simulate the climatological mean of the annual cycle in regional rainfall in 2050, we took the output from the AR4 GCM large-scale fields for the period 2000-2050, and fed the output into each EDM to obtain the downscaled regional precipitation for 2000-2050. The time series for each individual month (e.g., Jan 2001, Jan 2002 .... Jan 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.

## 2. Calculating threshold variables for risk assessment.

A second main focus of our project was to develop a risk assessment model to a) identify a climate variable with clear effects on rice productivity in Java and Bali based on the observational record; b) select a threshold for this variable beyond which the loss in productivity was significant; and c) determine the probability of exceeding this threshold under current and future (2050) climate conditions. Selecting 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. This earlier work underscored the important roles that variability in precipitation and its impacts on the timing of rice plantings and harvests play in the climate-agriculture story.

To identify specific threshold indicators for this study, we used least-squares regression models that relate crop production variables (yield, area, total production by season, timing of planting and harvest) to observed precipitation from 1979-2004. Rice planting and harvesting data for West, Central, and East Java and Bali were available from the Central Bureau of Statistics in Indonesia on a trimester basis (January-April, May-August, September-December) for the period 1979-2004. Rice production data were available from 1982/3-2003/4. Calendar year data were re-tabulated on a September-August crop year basis for our analysis. Precipitation variables were derived from daily rainfall data collected at regional rainfall stations throughout Java and Bali and reported in the NOAA Climate Prediction Center's Global Summary of the Day (GSOD) archive.

Our analysis showed that the date of monsoon onset was a particularly good predictor of ensuing crop-year rice production. We defined monsoon onset as the days past August 1 when accumulated rainfall equals 20 cm—the amount of moisture needed for crop establishment. August was chosen as the start date because it is typically the driest month across the archipelago. The effect of onset delay, shown in Figure 2 below, was determined by least squares regression of detrended rice production for a given trimester as a quadratic function of the monsoon delay. The coefficient on the onset variable reflects the effect on production of delaying onset by one day (relative to the average onset date). To get the percent effect of a 30-day onset delay on production, we multiplied the coefficient by 30 and divided the total by the average production for the region over the entire period.

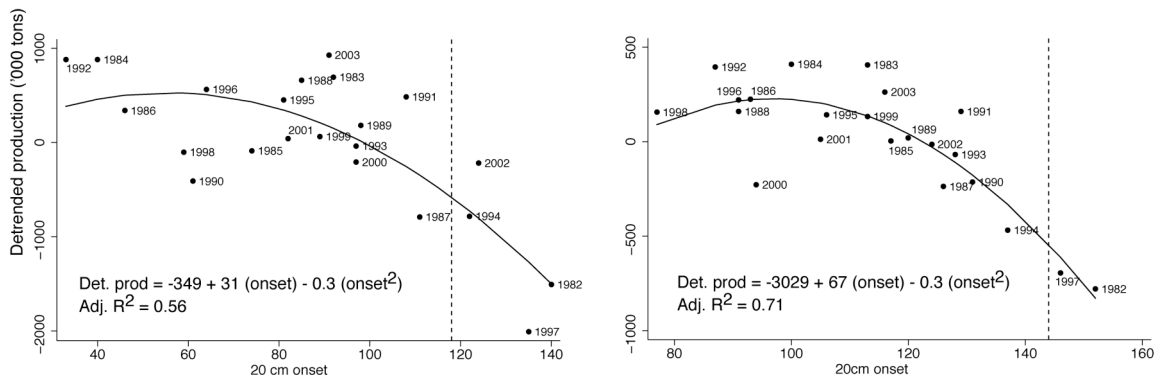


Figure 2. January-April rice production in relation to monsoon onset. Y-axis: time-detrended production, 1982/83-2003/4 (thousand metric tons). X-axis: days past Aug 1<sup>st</sup> when 20 cm of total rainfall are accumulated. Year labels correspond to the year of monsoon onset; production (harvest) occurs in the following year (January-April). Dashed lines represent the 30-day threshold. Left panel = West + Central Java. Right panel = East Java + Bali.

### 3. Assessing risks to Indonesian rice production under future climate change

With parts 1 and 2 in hand, we were then prepared to assess risks to Indonesian rice production from future climate change, in addition to quantifying their uncertainties. With ENSO variability superimposed onto 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.

Figure 3 shows the probability distributions of exceeding the threshold in 2050 by region, EDM, and emissions scenario. Each distribution reflects the combined output from 15-20 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 today. More importantly, the distribution indicates a substantially greater likelihood of exceeding the threshold for many models included in our analysis. Using the A2 emissions 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, there are some models that show a reduced probability of threshold exceedance.

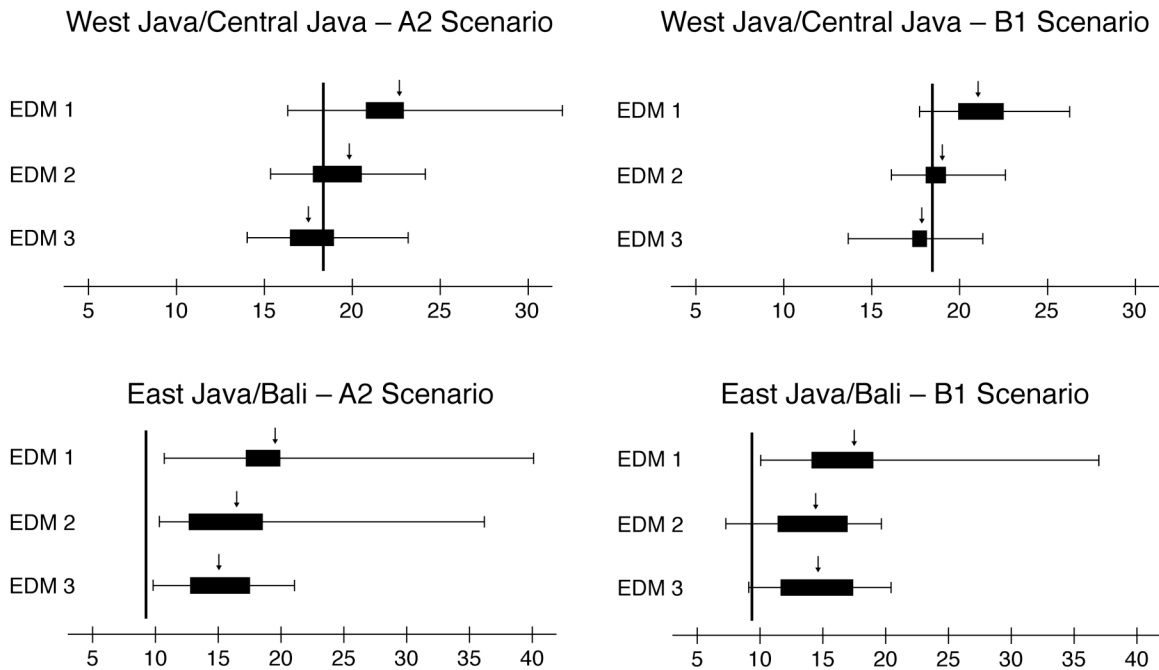


Figure 3. Likelihood of exceeding the 30-day monsoon threshold in 2050. The figures show the probability distribution for the three EDMs used in downscaling applied to all GCMs for each scenario. The probability distributions are divided into terciles, each containing output from one-third of the GCMs 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 small arrows indicate the mean future probability for all GCMs. The vertical lines show the observed probability for 1983-2004.

These results also provide insights into the nature of uncertainty in the model projections. Uncertainty in the future path of greenhouse gas emissions and their impact via climate forcing—illustrated by the differences between the A2 and B1 scenarios—are relatively insignificant. Less than half a century (2050) is too soon to see the broad climate effects of alternative technology and management approaches. On the other hand, uncertainty in the response of large-scale circulation 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 is today.

Given that most models project an increasing likelihood of a delayed monsoon onset that exceeds the threshold for significant impacts on rice production, to fully quantify likely outcomes for rice production we then want to know how the annual cycle in precipitation is 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.

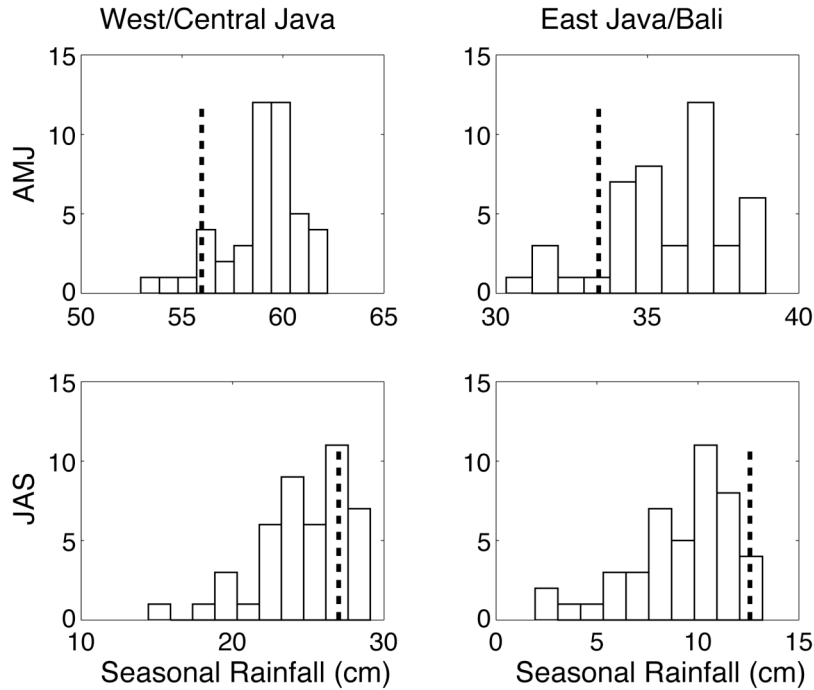


Figure 4: Summed precipitation for April-June (AMJ) and July-September (JAS) for the present climate (dashed line) and for the future predicted climate using the A2 scenario. The projected climates are shown as a probability distribution function, where 15 climate models have been downscaled using the three EDMs (for a total of 45 estimates).

Results in this area indicated that the projected peak monsoon precipitation will increase, rainfall during the dry season will very likely decrease, and the ending date of the monsoon will not change significantly. As a result, our existing threshold remains relevant, if not conservative, in 2050. Figure 4 shows the predicted change in total rainfall over Java and Bali for the periods April-May-June (AMJ, when the dry season planting typically occurs) and in July-August-September (JAS, the later period of the dry season when little rice is currently planted) for the A2 scenario. The combination of all GCMs and EDMs used in our analysis present 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 about 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 total rainfall to drop close to zero for the JAS season.

We drew three conclusions 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 our monsoon delay threshold probably could become quite conservative for measuring impacts of climate variability in 2050. An additional threshold of dry season total rainfall might therefore become important for future climate impact studies of Indonesian agriculture.

#### 4. Understanding the structural dynamics of ENSO with climate change

In our previous work, we assumed that the variability in precipitation over Indonesia due to ENSO in future climates was the same as in the present climate. This was a necessary assumption because only two of the twenty-three AR4 GCM models used to project the future climate have ENSO; hence, the interannual variability in the IPCC models is artificially muted. During the past year, we have been running experiments to relax this assumption. Specifically, we have been adding ENSO SST anomalies in the central Pacific to a range of projected mean state changes for 2050, and then forcing an atmospheric model with these SSTs to evaluate how the teleconnected signals associated with ENSO SST anomalies will change due to the changes in the mean state. These experiments have allowed an early understanding of how the impact of ENSO will change due to global warming due to changes in the ‘teleconnections’ (communicated through changing atmospheric motions) from the active ENSO region to far-field places, such as Indonesia .

#### 5. Bayesian analysis of El Niño risk related Indonesia rice production

The linkages between El Niño events, monsoon onset delays, reduced rice plantings, and extensions of the “season of scarcity” before the main rice harvest (*paceklik*) are important for policymakers concerned with domestic food security. We constructed a model to forecast El Niño conditions using Bayesian analysis in order to reduce uncertainty for food policy analysts over the course of the ENSO cycle. Essentially, Bayesian analysis was used to calculate the subjective probability that a certain year will be an El Niño year, and to update that probability as evidence of El Niño conditions—in the form of sea surface temperature anomalies (Niño 3.4 SSTAs)—accumulates over the course of the year. For example, Figure 5 presents Bayesian forecasts of the probability of an El Niño event occurring based on May-September SSTA data for the years 1980-1986; this period was chosen because of its strong El Niño and non-El Niño (neutral and La Niña) cycles. The figure also shows monthly SSTA data for the entire annual cycle to illustrate the accuracy of the forecast method. In general, Bayesian updating provides accurate forecasts of El Niño conditions by June/July.

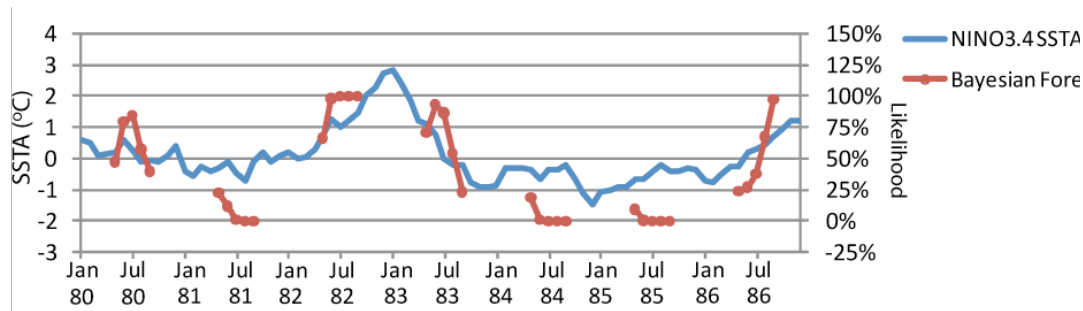


Figure 5: Niño3.4 SSTAs (blue line and left axis), and yearly Bayesian forecasts of the probability of a given year being an El Niño year (red line and right axis). Forecasts are based on May-September SSTAs.

However, as illustrated by 1980 and 1983, the forecast involves greater uncertainty for years in which SSTAs are positive in late spring but fall during the course of the summer. Forecasts for these particular years showed a rising probability of an El Niño event initially, but then the probability fell towards zero. Conversely, the forecast for 1986—a year in which SSTAs were negative at the start of the summer but quickly rose into El Niño territory—took longer to reach a high probability. Uncertainty over El Niño forecasts always decreases as the monsoon season begins in September/October.

Our analysis suggested that in years when the May to September SSTAs change direction, policymakers would be wise to take advantage of the Bayesian technique by remaining cautious in their prediction of ENSO conditions. Rather than jumping on the bandwagon that “an El Niño is coming” too soon, policymakers should wait until late August or September to confirm the climate trend. If they wrongly assume that El Niño conditions will prevail when in fact neutral ENSO conditions result in the end (Type II error), they are likely to spend unnecessary funds to import rice for the main harvest season—a move that could lead to excess rice in the market at a time when domestic farmers rely on relatively high prices for their incomes. Under such circumstances, the government might need to store excess rice in order to keep producer prices stable—another costly budget decision—or they might simply let prices drop which would benefit consumers but hurt producers. Conversely, if policymakers remain complacent in their forecast that no El Niño will develop when in fact one does (Type I error), the consequences could be equally if not more severe. Without arranging for rice imports or domestic reallocation within the country, policymakers could face rice shortages, higher food prices, food riots, and rising malnutrition among the poor.

The Bayesian forecast method developed in our study is straightforward, and we showed a variety of ways in which it could be improved to reduce the potential for Type I and II errors. For example, information from year (t-1) can be used to inform the initial forecast for year (t) because, for example, there is a low probability that one strong El Niño year will be followed immediately by a second strong El Niño year. Additional information could also be used in the updating process, such as monthly SOI data or SSTA data from a broader geographic band (e.g., 30°N to 30°S), to inform the forecast. Finally, a more complex approach to Bayesian updating can be applied to ENSO forecasting by

combining forecasts generated from a combination of dynamic and empirical approaches, e.g., relying on the integration of historical information and dynamic model forecasts. We are currently using our Bayesian model to track the development of El Niño conditions in Indonesia, with the aim of advising food policy analysts of expected conditions during the 2009-2010 crop year.

Over the longer-term, our Bayesian approach could be used to help Indonesian policymakers anticipate ENSO impacts in a warmer world. Given the projections in our study of a significant change in the annual cycle of precipitation in the region, policymakers could use updated climate information for adaptation; that is, they might want to invest in water storage facilities (reservoirs and linked irrigation systems) to take advantage of periods of more intense rainfall and cover longer dry periods. They also might want to invest in drought tolerant crops, or provide incentives for alterations in cropping systems that match both climate conditions and market demand. In this particular case, the Bayesian null hypothesis would be a change in the annual cycle of precipitation that affects crop production, food availabilities, and incomes throughout the year (as projected in Figure 3). The prior would be established on the basis of the observed annual cycle going back in time for decades, and this prior would be updated with new information as the years progressed. The likelihood of the null hypothesis being true could thus increase over time as more information became available on the pattern of rainfall over the course of the year. This analysis is very different from the Bayesian analysis of El Niño events described above for the short term, because a long-run change in the climate's mean state has not yet been fully established (beyond historical patterns of variability).

### **Training, outreach, and related activities**

The research on Indonesia outlined above gave rise to many teaching and outreach activities, in addition to provoking new research directions and output.

#### **1. Collaboration and dissemination of research with Indonesian colleagues**

Throughout the course of the project, we communicated our results to the Food Security Division of the Ministry of Agriculture (DEPTAN), the Planning Ministry (BAPPANAS), and the Central Bureau of Statistics (BPS). In November 2006 we formally presented the key results of our climate change research to the Agricultural University in Bogor Indonesia, the Indonesian Ministry of Agriculture in Jakarta, and the Indonesian Department of Meteorology in November 2006. Since the project ended, we have continued to update our Indonesian colleagues with climate information, and they are using our short-term forecasts for food policy planning. Overall, our work received quite a bit of attention in Indonesia, and was reported on the front page of the *Jakarta Post* when our first main paper (Naylor et al, 2007, in *PNAS*) was first released. We also presented various aspects of the work at numerous environmental and climate seminars around the US.

## 2. Extensions to the Philippines and China: A regional study of ENSO-rice relationships

Based directly on our Indonesia work, we conducted similar research in the Philippines and showed that El Niño conditions similarly cause drought conditions and reduced rice production (Roberts et al., 2009). We also received an additional NSF grant to extend the research to China (NSF grant number 0624359), a project entitled “Impacts of El Niño-Southern Oscillation (ENSO) Events on Chinese Rice Production and the World Rice Market”. Early analysis suggested the ENSO in China would be the mirror image of Indonesia and the Philippines – that is, that warm ENSO events increase rainfall in China, raising rice production, with cool ENSO events doing the reverse. As a result, the regional rice market would be neutral, implying no significant increase in rice price during an El Niño year.

Building on our risk assessment framework, the China work seeks to quantify these effects of ENSO on Chinese rice agriculture, and to adapt a global trade model to understand how ENSO effects regional rice markets, through its effects in China, Indonesia, and the rest of Southeast Asia. We are in the final year of that grant.

## 3. Outreach of methods to the Wisconsin Initiative on Climate Change Impacts (WICCI).

Relying on the experiences that grew out of our NSF work, PI Vimont helped design a new initiative to assess the impacts of climate change in Wisconsin - the Wisconsin Initiative on Climate Change Impacts (WICCI). Our experience through the NSF grant demonstrated the need for a collaborative, iterative structure between climate scientists, impacts scientists, and policy makers in the impacts assessment process rather than a top-down framework in which the climate information drives the research. As such, Vimont helped to develop a "boundary institution" that facilitates interaction between climate science, impacts science, and policy from the highest levels in the state (the WICCI Advisory Council has had input from the Wisconsin Governor's office, and includes leaders of Wisconsin's industry, NGO's, and the political arena) to individual working groups (each of the eleven currently active working groups consists of a team of scientists who collectively define the research problem - just as was done in our NSF proposal). Since June 2007, the WICCI has grown from a simple idea into a state-wide initiative that partners the University of Wisconsin with the Wisconsin Department of Natural Resources, and numerous other state agencies and institutions. The WICCI now includes collaborations with over 120 scientists around the state. The rapid expansion of the project can largely be attributed to the institutional framework that borrowed heavily from the experience gained from our NSF project. In short, the WICCI allows a type of interdisciplinary research to occur that could not happen in the absence of a trans-boundary institutional framework (a similar framework existed on a much smaller scale in our NSF project).

WICCI is now a catalyst for new proposals on climate impacts to federal and state agencies. The WICCI has secured funding from the Wisconsin Focus on Energy Program to develop a set of downscaled daily precipitation and maximum and minimum temperature over Wisconsin using a novel statistical methodology that is motivated by

the EDMs in the present project. This climate work has also motivated involvement in five additional proposals (as collaborators in providing climate information) to federal agencies. Additionally, the Wisconsin Department of Natural Resources is now allocating employee time to work on WICCI. Vimont has given 10-15 talks in the last two years on climate impacts in Wisconsin, and on the climate impacts assessment process.

#### 4. Teaching and development

We had both positive and negative experiences on the teaching and development side of the grant. On the positive end, the interdisciplinary research framework we developed was used in graduate training in our three universities: 1) at Stanford University in the Interdisciplinary Ph.D. program in Environment and Resources (IPER) and the Department of Environmental Earth Systems Science; 2) at the University of Washington's Earth Institute and the Department of Atmospheric Sciences; and 3) at the University of Wisconsin in the Center for Climatic Research (part of the Institute for Environmental Studies) and the Department of Oceanic and Atmospheric Sciences. In addition, Naylor, Battisti, and Vimont frequently traveled to each other's universities to team-teach classes on the topic. In addition, the work was used as a template for teaching interdisciplinary research methods in Stanford University's undergraduate Goldman Honors Program in Environmental Science, Technology, and Policy, and in the National Centre of Competence in Research (NCCR) Summer School, sponsored by the Swiss National Science Foundation.

We had less success with turning the project into specific PhD theses. Naylor mentored a student for two years who was then diagnosed with an illness that prohibited her from traveling to Indonesia for fieldwork. Similarly, Vimont mentored a student for two years who had family-related health issues and had to stop out. Nonetheless, Naylor was able to mentor a post-doc (Michael Mastrandrea, mainly on the Bayesian analysis) and Battisti and Vimont also took on a student for related research, Rob Nicholas, who will finish his PhD in summer 2010. All of the PIs also mentored a pre-doc at Stanford, Marshall Burke, who co-authored the lead publication in *PNAS* and will start a PhD in August 2009 in the Agriculture and Resource Economics Department at the University of California in Berkeley (awarded the top scholarship).

#### 5. Extension of research to include temperature effects of global climate change.

The PIs have continued to collaborate and launch new areas of research together that are not directly related to this topic. For example, Battisti and Naylor collaborated on a study assessing future climate impacts on agriculture, using historical analogies to gauge damage in the absence of adaptation (Battisti and Naylor, 2009). Battisti and Vimont have begun a new NOAA-funded project to examine how ENSO itself will change due to global warming (extensions are planned to include the teleconnected impacts of a changed ENSO on Indonesia, China and the southwest US). The team expects to continue collaborations in new areas of climate science, agricultural production, and food security

in the future.

6. Advances in climate science and our understanding of climate change science.

We found that the climate models systematically project precipitation in the Indonesian monsoon will become more intense and – more important and more serious in terms of impacts – the rainy season will become shorter and the subsequent dry season will become drier. Our approach to understanding changes in tropical precipitation was novel and our findings were somewhat surprising and robust. The success of our approach has inspired others to re-examine monsoons elsewhere using a similar framework (prior to our work, the IPCC had only focused on the changes in the rate of rainfall *during* the rainy season). This has led to some major advances in understanding how monsoons throughout the tropics will change due to global warming. In turn, this has already led to a large reduction in the uncertainty of the projections of tropical precipitation patterns – in particular, in the Sahel – over those expressed only two years ago in the most recent IPCC report.

**Publications**

- Battisti, D. and R. Naylor, “Historical warnings of future food insecurity with unprecedented seasonal heat”, *Science* vol. 323, January 9 2009.
- Naylor, R., Battisti, D., Falcon, W., Vimont, D., Burke, M. (2007) “Assessing Risks of Climate Variability and Climate Change for Indonesian Rice Agriculture”, *PNAS* 104, 19: 7752-7757.
- Naylor, R. and M. Mastrandrea, “Coping with climate risks in Indonesian rice agriculture: a policy perspective”, in J. A. Filer and A. Haurie (eds.) *Handbook on Uncertainty and Environmental Decision Making*: Springer International Series in Operations Research and Management Science (in press), March 2009.
- Roberts, M., Dawe, D., Falcon, W., and R. Naylor, “El Nino-Southern Oscillation impacts on rice production in Luzon, the Philippines”, *Journal of Applied Meteorology and Climatology* (in press), 2009.
- Vimont, D., Battisti, D. and R. Naylor, “Downscaling Indonesia precipitation using large-scale meteorological fields”, (re-submitted (after favorable initial review) to *International Journal of Climatology*), November 2008.