Prediction of Rice Production in the Philippines Using Seasonal Climate Forecasts

NAOHISA KOIDE*

Quantitative Methods in the Social Sciences, Columbia University, New York, New York

ANDREW W. ROBERTSON, AMOR V. M. INES, JIAN-HUA QIAN, AND DAVID G. DEWITT

International Research Institute for Climate and Society, Earth Institute at Columbia University, Palisades, New York

ANTHONY LUCERO

Philippines Atmospheric, Geophysical and Astronomical Services Administration, Quezon City, Philippines

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ABSTRACT

Predictive skills of retrospective seasonal climate forecasts (hindcasts) tailored to Philippine rice production data at national, regional, and provincial levels are investigated using precipitation hindcasts from one uncoupled general circulation model (GCM) and two coupled GCMs, as well as using antecedent observations of tropical Pacific sea surface temperatures, warm water volumes (WWV), and zonal winds (ZW). Contrasting cross-validated predictive skills are found between the “dry” January–June and “rainy” July–December crop-production seasons. For the dry season, both irrigated and rain-fed rice production are shown to depend strongly on rainfall in the previous October–December. Furthermore, rice-crop hindcasts based on the two coupled GCMs, or on the observed WWV and ZW, are each able to account for more than half of the total variance of the dry-season national detrended rice production with about a 6-month lead time prior to the beginning of the harvest season. At regional and provincial levels, predictive skills are generally low. The relationships are found to be more complex for rainy-season rice production. Area harvested correlates positively with rainfall during the preceding dry season, whereas the yield has positive and negative correlations with rainfall in June–September and in October–December of the harvested year, respectively. Tropical cyclone activity is also shown to be a contributing factor in the latter 3-month season. Hindcasts based on the WWV and ZW are able to account for almost half of the variance of the detrended rice production data in Luzon with a few months’ lead time prior to the beginning of the rainy season.

1. Introduction

Rice is the most important crop for the people of the Philippines. Because the fluctuation in domestic rice production has significant impacts on food security, especially for the poorest people, its stabilization is a critical concern for the Philippines in terms of food security and the alleviation of poverty (Dawe et al. 2006, 2009).

Paddy rice is known to be one of the most highly susceptible cereal crops to climate variability because of its high water requirements. Relationships between rice and climate are well documented by past research (e.g., Lansigan et al. 2000; Naylor et al. 2001; Selvaraju 2003; Lansigan 2005; Dawe et al. 2009; Roberts et al. 2009). In the case of the Philippines, much attention has been paid to El Niño–Southern Oscillation (ENSO) because of its large impact on the Philippine climate and the demonstrated impacts of ENSO on Philippine rice production. For example, Lansigan et al. (2000) indicated that, in El Niño years, rainy-season sowing, which generally occurs around May, could be delayed to mid-August depending on the degree of climate variability. Roberts et al. (2009) found different impacts of ENSO on the January–June “dry” season and the July–December “rainy” season rice production of irrigated and rain-fed systems in Luzon, respectively; namely, a statistically significant relationship has been identified between dry-season rice production in Luzon and sea surface temperature (SST)
anomalies averaged over the Niño-3.4 region (5°N–5°S, 120°–170°W) for July–September (JAS) of the year before the January–June harvest, but no significant correlations have been found between the July–December rainy-season production and Niño-3.4 SST anomalies.

Thus, past research suggests that it may be possible to forecast aspects of Philippine rice production based on climate information alone. Such forecasts could potentially benefit decision making from national, regional, and local governments to local farmers (Lansigan 2005). Previous studies have discussed the potential of seasonal climate forecasts for forecasting climate-sensitive crops in other regions (e.g., Baigorria et al. 2008, 2010; Hansen et al. 2004; Mishra et al. 2008; Semenov and Doblas-Reyes 2007; Ines et al. 2011).

The goal of this paper is to develop seasonal climate forecasts tailored to Philippine rice production for the dry and rainy seasons, at three different spatial scales (national, regional, and provincial), and to assess and quantify potential predictive skills by means of retrospective forecasts. We construct crop prediction models that are 1) purely empirical, based on observed antecedent climate conditions, as well as 2) semiempirical, based on general circulation model (GCM) forecasts of precipitation over the Philippines. We apply a cross-validated regression approach in which the predictands are historical records of rice yield, production, or area harvested at the national, regional, and provincial levels, and the predictors are antecedent climate variables, or GCM precipitation forecasts. To our knowledge, this is the first comprehensive prediction analysis of Philippine rice production covering the entire region at national, regional, and provincial levels, and considering both irrigated and rain-fed rice systems, with state-of-the-art climate forecasts from coupled and uncoupled GCMs. Our results also serve to quantify the value added from GCM forecasts for crop forecasting, compared to purely empirically models. The regression models are based on cross-validated multiple linear regression, principal component regression, and canonical correlation analyses, following previous studies (e.g., Hansen et al. 2004).

The paper proceeds as follows. Section 2 describes the rice production and the climate in the Philippines. The datasets used in the paper are described in section 3. Our methodologies and results are presented in section 4. A summary and discussion are presented in section 5.

2. The study region

a. Rice production

Rice in the Philippines is typically planted by transplanting seedlings in puddled, bunded fields, where a constant height of water is maintained throughout the growing season. This way of water management provides a suitable environment for optimal rice growth and for weed control (de Datta 1981). Rice production has been increasing for more than five decades through the development of arable lands, construction of new irrigation systems, improvement of existing irrigation systems, and adaptation of new technologies such as modern rice varieties and improved fertilizer usage (Kikuchi et al. 2003). Figure 1a shows the increasing trend of the annual rice production on top of the interannual variability. Figure 1b also shows that the irrigated annual yields started increasing rapidly in the early 1970s and continue to exhibit a strong increasing trend, in contrast to the relatively small increasing trend of the rain-fed yields for the period. The total area harvested has been increasing due to the creation of new agricultural lands through expanding the irrigated area, while that of rain-fed systems has been gradually decreasing, caused possibly by its conversion to either non-agricultural uses or irrigated area, as shown in Fig. 1c.

Luzon is the main rice producer of the Philippines (Fig. 2a). Most rice-growing regions of Luzon and Mindanao are heavily irrigated, while regions in the central Philippines consisting of smaller islands still produce about half of their rice with rain-fed systems (Fig. 2b). Most irrigation systems in the Philippines are run-of-the-river systems; that is, the water supply is not buffered by storage reservoirs, but by the natural flow of the rivers, although there are some large irrigation projects with storage dams (Ongkingco et al. 1982). The rainy-season rice in the Philippines is planted at the onset of the summer monsoon, which generally occurs in May, and is harvested around September–November. The planting of dry-season rice follows right after the harvest of the rainy-season rice for utilization of rainfall at the end of the rainy season (e.g., Roberts et al. 2009).

b. Climate

The Philippines, consisting of 7107 islands, is within the western North Pacific Ocean (WNP) southwest summer and northeast winter monsoons domain (Wang and Ho 2002). The Philippine climate varies widely by region due to its complex topography and is classified into four types by the Philippines Atmospheric, Geophysical and Astronomical Services Administration (PAGASA). Type I has a distinct summer monsoonal wet season from May to October and a dry season from November to April. Most western regions belong to this type. Type II, on the contrary, has no clear dry season with maximum rainfall in November–December associated with the northeast winter monsoon. Most of the northeastern regions are categorized into this
Type III is an intermediate band between types I and II. It has maximum rainfall from May to October with an unclear but relatively dry season from November to April. Most southern areas belong to type IV, which has evenly distributed rainfall throughout the year (Figs. 3a,b). Moron et al. (2009a) also classified the Philippine rainfall patterns into two groups using a $k$-means clustering method: a west coast region with clear dry seasons from November to April and an east coast region without a dry season during the period.

Several previous studies have addressed the mechanisms and the predictability of the summer monsoon and its onset over the northwest Pacific and the Philippines during May–June (e.g., Wang and Ho 2002; Akasaka et al. 2007; Moron et al. 2009a). Interannual variability of the Philippine climate is dominated by ENSO. PAGASA summarizes the potential impacts as follows. During the warm (cold) phase of ENSO, 1) the rainy season is shorter (longer) because of the delayed (normal or early) monsoon onset and the early (normal or late) termination, 2) there is weak (strong) monsoon activity, 3) fewer (more) cyclones pass through the Philippines, 4) rainfall is below (above) normal, and 5) temperatures are above (below) normal. More recently, however, Lyon and Camargo (2009) revealed a seasonal reversal in the ENSO rainfall signal over the Philippines between JAS and October–December (OND), with below (above) average rainfall in JAS and above- (below-) average rainfall in OND during the warm (cold) phase of ENSO. A warm (cold) phase of ENSO induces drier (wetter) conditions in OND in almost the entire region with especially strong impacts in the central Philippines. Significant positive correlations between several stations in the central Philippines with the Niño-3.4 index are observed in JAS. It is revealed that the development of the low-level westerlies over WNP during the boreal summer, through the enhancement of

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**Fig. 1.** (a) Annual rice production (t), (b) yield (t ha$^{-1}$), and (c) area harvested (ha) of all ecosystems (blue), irrigated systems (red), and rain-fed systems (pink) in the Philippines (1970–2007).
WNP summer monsoon, increases the rainfall around the region (Lyon and Camargo 2009).

3. Data

a. Rice data

National, regional, and provincial data on rice production, yield, and area harvested of irrigated systems, rain-fed systems, and all ecosystems, from 1970 to 2007, were downloaded from the Philippine Rice Statistics e-Handbook published as a collaborative project of the Philippine Rice Research Institute and the Philippines Bureau of Agricultural Statistics (http://dbmp.phlirice.gov.ph/Ricestat/Statmonth%20data/index.html). The Philippines has 17 administrative regions (Fig. 3b) and 80 provinces; however, this dataset includes 16 administrative regions [the National Capital Region (NCR) is not available] and 73 provinces. Here, all ecosystems include irrigated and rain-fed systems, as well as highlands. However, rice production in the highlands is negligible and is thus not considered in this study. This dataset is partitioned into two seasons, January–June and July–December, which approximately correspond to the periods of rice harvest for the dry and rainy seasons, respectively. Rice data for January–June and July–December are referred to as dry-season and rainy-season rice data, respectively, hereinafter. Because of the non-existence of regional data for regions I, IX, XI, and XII (Fig. 3b), they were calculated from available provincial data. Note that the rice data from regions IX, XI, and XII are incomplete because of the lack of provincial data: provincial rice data for Zamboanga Sibugay in region IX, Compostela Valley in region XI, and Sarangani and South Cotabato in region XII are not available. Rice data for region IV were decomposed into region IV-a and IV-b using the provincial rice data; rice data for region IV-b were obtained as the difference between those for region IV and those for region IV-a, which were calculated from the provincial data. The rice data for 1970–76 were neither used in the correlation analysis with rainfall, nor in the predictability analysis, because of the unavailability of many of the climate data records and forecasts for the period.

b. Climate data

A 77-station network of daily rainfall observations from 1977 to 2004, obtained from PAGASA, is used in the paper (Fig. 3a). A single-point weather generator was used to fill the small number of missing values (<3%), which were mostly scattered in space and time, using a gamma distribution applied to each station individually, with parameters estimated for each calendar month separately (Moron et al. 2009a). A wet day is defined here as a day with more than 1 mm of rainfall. Multipoint geospatial weather generators would be an option for less complete datasets (e.g., Baigorria and Jones 2010; Brissette et al. 2007).
The Niño-3.4 index from 1969 to 2008, calculated by the National Oceanic and Atmospheric Administration (NOAA)/Climate Prediction Center, and an index of equatorial Pacific heat content (the integrated warm water volume; WWV) above the 20°C isotherm and averaged between 5°N and 5°S and between 120°E and 80°W (Meinen and McPhaden 2000) from 1980 to 2008, calculated using NOAA Tropical Atmosphere–Ocean (TAO) buoy data, were used as empirical predictors. Data on tropical cyclones (TCs) for the period 1977–2007 were downloaded from the U.S. Navy’s Joint Typhoon Warning Center western North Pacific best-track data. In this study, only TC data within 100 km of the coastline of the Philippines were used. Surface zonal wind (ZW) anomalies averaged between 2°S and 2°N and between 180° and 220°E for the period 1980–2008 were also used as predictors and were obtained from the NOAA Atlas of Surface Marine Data 1994 (da Silva et al. 1994) and the Tropical Ocean and Global Atmosphere (TOGA)–TAO array. Zonal wind anomalies over the region are important for ENSO development (Izumo et al. 2010).

c. Seasonal prediction models

For predictability analysis and building forecast models for rice, we used retrospective seasonal climate forecasts (also referred to as hindcasts) made with three GCMs, chosen as representative of the systems (coupled and uncoupled) and used in current seasonal climate forecasting. We use the uncoupled Max Planck Institute ECHAM4.5 atmospheric GCM (AGCM; Roeckner et al. 1996) forced with empirically predicted constructed analog (CA) SSTs (ECHAM-CA; Van den Dool 1994; Li et al. 2008), with 24 ensemble members for each year from 1981 to 2007. In addition, we use two coupled GCMs: the National Centers for Environmental Prediction (NCEP) Climate Forecast System, version 1 (CFS), a fully coupled ocean–land–atmosphere dynamical seasonal prediction system (Saha et al. 2006), with 15 ensemble members from 1981 to 2007, and a coupled GCM consisting of the ECHAM4.5 AGCM and the Geophysical Fluid Dynamics Laboratory (GFDL) Modular Ocean Model, version 3 (MOM3; Pacanowski and Griffies 1998), with 9 ensemble members from 1982 to 2007 (ECHAM-MOM; DeWitt 2005). For each GCM, the ensemble mean over all of the available ensemble members was taken at the outset. ECHAM-CA and ECHAM-MOM were both run at T42 spatial resolution (~300-km grid), and the CFS was run at T62 (~200-km grid). Both ECHAM-MOM and CFS were run without flux correction. Physical parameterization details can be found in Roeckner et al. (1996) and Saha et al. (2006), respectively.
4. Methodology

a. Detrending and normalization of rice data

Rice production is influenced by nonclimatic factors such as changes in technology. Here, we assumed that nonclimatic factors influence rice production at lower frequencies and that such trends can be removed from the rice data time series using a low-pass spectral smoothing filter, leaving those signals influenced by climate. We used a Butterworth low-pass filter with a 10-yr cutoff period to detrend the rice data. The cutoff period was chosen based on similar published and unpublished studies (e.g., Baigorria et al. 2008). Running averages of 7, 9, and 11 yr were also calculated, leading to results similar to those found with the Butterworth filter. Residuals of rice data were then normalized as deviations from the trend component divided by the trend \( \left[ \text{observed value} - \text{trend} \right]/\text{trend} \), in order to focus on rates of change in the rice data.

The distribution of the rice data residuals often departs from normality. Prior to the correlation analysis with climate variables, a Box–Cox transform (Box and Cox 1964) was applied to the residuals of the rice data to correct the departures from normality. However, very similar results were obtained without the Box–Cox transform (not shown). Prior to regression-model building, a quantile–quantile mapping of the empirical distribution to a normal deviate was used to normalize the rice data residuals (with no Box–Cox transformation).

b. Measures of spatial coherence of station rainfall

Previous studies have shown that the spatially coherent component of seasonal rainfall anomalies at the station scale in the tropics (Haylock and McBride 2001; Moron et al. 2006, 2007) and the Philippines (Moron et al. 2009a) tends to reflect the impact of large-scale climate forcings such as ENSO; thus, higher spatial coherence tends to indicate higher seasonal predictability. Two different measures are used here as the indicators of spatial coherence on station rainfall, namely the interannual variance of the standardized anomaly index \( \text{var}(\text{SAI}) \), where the standard anomaly index (SAI; Katz and Glantz 1986) is defined as the station average of the normalized station time series of seasonal average rainfall, together with the number of spatial degrees of freedom (DOF; Fraedrich et al. 1995). For example, if the seasonal rainfall between all stations is perfectly correlated, \( \text{var}(\text{SAI}) = 1 \); if the seasonal rainfall of all stations is independent, \( \text{var}(\text{SAI}) = 1/M \), where \( M \) is the number of stations (Katz and Glantz 1986; Moron et al. 2006). The DOF, an alternative measure of spatial coherence to \( \text{var}(\text{SAI}) \), estimates the number of independent variables in a dataset in terms of empirical orthogonal functions (EOFs); higher (lower) values represent lower (higher) spatial coherence. The DOF and \( \text{var}(\text{SAI}) \) are consistent estimators of spatial coherence (Moron et al. 2007).

Using these two indicators, the spatial coherence of seasonal rainfall amount \( S \), occurrence or number of wet days \( O \), and mean intensity on wet days \( I \) was examined; note that \( S = OI \).

c. Regression models and predictor variables

Cross-validated regression models were built for national rice production using various climate variables as predictors. This method of model building and testing is appropriate when the length of the available time series, given by the overlapping portion of the predictor and predictand time series (here, 1981–2007), is small, allowing us to maximally use the data available for building regression models (e.g., Tippett et al. 2005).

To avoid biased estimation of cross-validated skills caused by overfitting, 5-yr contiguous samples were withheld to develop the regression equation where the forecast is validated for the central year of the withheld years. Such an omission of the years on either side of the forecast year ensures the independence between a dataset for a training period and that for a test period by guarding against leakage of the signal from adjacent years.

Three different types of linear regression models were used: multiple linear regression (MLR), principal component regression (PCR), and canonical correlation analysis (CCA). PCR is a regression analysis for a univariate predictand that uses a subset of principal components (PCs) of the predictor set, so as to account for a large fraction of the predictor variance within a few independent components. CCA is a multivariate statistical method of identifying linear relationships between two sets of multidimensional variables, based on low-dimensional PC subsets of both the predictor and predictand datasets (Barnett and Preisendorfer 1987; Barnston and Smith 1996). Through the use of a small set of PCs as predictors, both PCA and CCA overcome problems with multicollinearity between predictors and the multiplicity arising from high-dimensional predictor fields. Here, the PC subsets selected for PCR and CCA were determined so as to maximize the average skill under cross validation. All of the analyses were performed using the Climate Predictability Tool (CPT) software (http://iri.columbia.edu/climate/tools cpt).

Climate variables selected as empirical predictors are the Niño-3.4 index and a two-dimensional predictor consisting of the WWV and ZW indices (section 3b). The WWV and ZW anomalies play key roles in the ENSO cycle, with El Niño events being accompanied by
positive WWV and ZW anomalies (Izumo et al. 2010); we refer to this bivariate predictor as WWV and ZW in the following. The regression coefficients of WWV and ZW are determined by MLR. In addition to these empirical ENSO indices, we also use the ensemble-mean hindcasts of seasonally averaged gridded precipitation over the Philippines (0°–25°N, 110°–130°E) from the three GCMs (i.e., ECHAM-CA, ECHAM-MOM, and CFS).

The purely empirical prediction models are based on MLR, using the empirical predictors averaged over the 3-month period prior to the month in which the forecast is made. For instance, for a forecast made in June, the predictors are averaged over the preceding MAM period. In the case of the GCM-based semiempirical models, we use PCR or CCA with the GCM’s predicted gridded precipitation field over the Philippines as predictors. The GCM is initialized on the first day of the month, and the forecasts of precipitation for the 3-month period prior to the rice production season are selected as the predictors. For example, the skill of June forecasts of the following January–June rice production season is based on the GCM’s OND precipitation anomalies over the Philippines, predicted on 1 June, with the following January–June rice production as the predictand.


d. Tropical cyclone activity in and around the Philippines

Rice production in the Philippines is severely affected by tropical cyclones (Lansigan 2005). Since most tropical cyclones pass over the central and northern Philippines, their impact is expected to be largest there. To examine the impacts of tropical cyclone activity on the rainy-season yields, we introduced accumulated cyclone energy (ACE; Bell et al. 2000) as an index of tropical cyclone activity because of its usefulness for correlation and regression analysis with the other climate variables (Camargo and Sobel 2005; Camargo et al. 2007). The ACE is defined as the sum of the squares of the estimated 6-hourly maximum sustained wind speed in which the cyclone is rated as either a tropical storm or greater (tropical depressions are not included in this analysis); this accounts for the number, intensity, and duration of tropical cyclones during a given typhoon season, all of which are likely to have impacts on rice production. In this study, we used ACE within 100 km of the coast of the Philippines during the main tropical cyclone season in the Philippines, from July through December (Lyon and Camargo 2009), for the period 1977–2007.

e. Analysis procedure

The analysis in this study proceeded as follows. First, the predictability of rainfall over the Philippines was examined in terms of its spatial coherence. Impacts of ENSO on rainfall over the Philippines were also investigated. Second, the rainfall season maximally correlated with dry-season (January–June) or rainy-season (July–December) rice production at the national level was identified through lag correlations between the all ecosystem rice production, yield, and area harvested of each season and SAI of $S$ from year$(-1)$ to year(0), where year(0) indicates a year of harvest and year$(-1)$ indicates the previous year. Here, the 3-month-averaged SAI of $S$ of the 77 stations was used as a representative index of the rainfall over the Philippines (Katz and Glantz 1986). Then, to examine predictive skills in the rice production of each season at the national level, the best predictors for the national rice production of all ecosystems based on cross validation were explored among 3-month averages (at various lead times) of various climate variables (i.e., the Niño-3.4 index, WWV, and ZW), as well as predicted precipitation over the Philippines from the three GCMs for the dry season, and WWV and ZW for the rainy season. Finally, using the best predictors with the longest lead times at the national level (i.e., predicted precipitation over the Philippines from CFS and ECHAM-MOM initiated on the previous 1 June for the dry season, and WWV and ZW in the previous DJF for the rainy season), predictive skills at the regional and provincial levels were investigated. Note that regression models for the rainy season using WWV plus ZW at regional (provincial) levels were built with MLR on a region (province) by region (province) basis.

5. Results

a. Spatial coherence and potential predictability of rainfall

Figure 4 shows the potential predictability of Philippine station rainfall in terms of the spatial coherence of $S$, $O$, and $I$. Both the var(SAI) and DOF indicate a higher spatial coherence of $S$ and $O$ from September–November (SON) through April–June (AMJ), followed by a lower coherence from May–July (MJJ) through August–October (ASO). These two half-years coincide with the main dry and rainy seasons, respectively. On the contrary, the spatial coherence of $I$ is low throughout the year, suggesting lower potential predictability of mean rainfall intensity throughout the year.

The seasonal cycle of correlations between the SAI of $S$, $O$, and $I$ and the Niño-3.4 index is shown in Fig. 5. All
three average rainfall quantities are negatively correlated with the Niño-3.4 index ($p < 0.05$) from SON to AMJ when the spatial coherence of $S$ and $O$ is high. Reversal of correlation between ENSO and rainfall was also found from JAS through ASO, though the correlations with the Niño-3.4 index are not statistically significant. It is interesting to note that the strength of the correlation of mean intensity with ENSO is comparable to that of the rainfall frequency, while the spatial coherence of the mean intensity is much lower that of the rainfall occurrence frequency.

The above analysis shows the distinct difference in potential predictability of rainfall in the Philippines between the dry and rainy seasons. Rainfall in the dry season, with high spatial coherence and strong negative correlations with the Niño-3.4 index, is potentially predictable at the station level, while that in the rainy season, with low spatial coherence and weak positive correlations with the Niño-3.4 index, is less predictable. A similar relationship among spatial coherence, predictability, and ENSO has also been found in Indonesia (Haylock and McBride 2001; Moron et al. 2009b).

b. Dry-season predictability (January–June)

1) RELATIONSHIP BETWEEN RICE PRODUCTION AND RAINFALL

Lag correlations between national rice production, yield, and area harvested and the time series of the SAI of $S$ from year$(-1)$ to year$0$, are shown in Fig. 6. For both irrigated and rain-fed systems, the peak correlations of the national rice production, yield, and area harvested with the SAI were found a few months before the beginning of the harvest period [i.e., OND of year$(-1)$], which approximately coincides with the planting period. Such high correlations ($r > -0.7$–0.8; $p < 0.01$) suggest that the total amount of OND rainfall is a critical climatic factor for dry-season rice planting in the Philippines. Similar but overall slightly weaker 3-yr lag correlations with the SAI of $O$ and $I$ were also found (not shown).

The peak correlations of the national rain-fed yield and area harvested of rain-fed systems with the SAI are higher than those of the irrigated system. Such differences between the two systems might be related to the closer dependence of rain-fed systems on rainfall (e.g., Sawano et al. 2008; Fukui et al. 2000). Higher sensitivity of rain-fed systems in the dry season to rainfall than irrigation systems was also found by Roberts et al. (2009).

At the regional level, correlations of rice production, yield, and area harvested of each system with the SAI (pink lines in Fig. 6) are generally weaker than those at the national level, while they also have peaks of positive correlations with the SAI in OND, similar to the trend at the national level. Higher dependencies of rain-fed systems on rainfall than irrigated systems are also observed in most regions.

2) PREDICTABILITY OF DRY-SEASON RICE PRODUCTION

(i) National level

As shown in the previous section, interannual variability of national dry-season rice production of irrigated and rain-fed rice systems depends strongly on rainfall from October of year$(-1)$ to March of year$0$ (Fig. 6). High predictability of rainfall during the period, as well as its strong dependence on ENSO shown in Figs. 4 and 5, suggest the potential predictability of dry-season rice production with climate information.
Figure 7 shows the cross-validated Pearson correlation skill, defined by the correlation between the time series of the observed data and the time series of cross-validated hindcasts, based on 3-month averages (at various lead times) of the Niño-3.4 index, WWV and ZW, as well as predicted precipitation over the Philippines from the three GCMs. The results demonstrate that the combination of WWV and ZW shows very high predictive skills ($r > 0.7$) even half a year before the beginning of the harvest period. The two coupled models show just as high predictive skills as those of WWV and ZW, and maintain these high skill levels even when initialized in June of the year ($-1$). In other words, more than half of the total variance of the national rice production in the dry season can be predicted several months prior to the planting, which generally takes place around October of year ($-1$). On the contrary, the predictive skill of the Niño-3.4 index and the uncoupled model, ECHAM-CA, decrease gradually as the lead time increases, and fall below 0.4 after half a year of lead time.

Figure 8 shows the time series of cross-validated hindcasts of national dry-season all-ecosystem rice production anomalies, obtained using PCR of OND precipitation forecasts from the coupled GCMs initialized on 1 June of year ($-1$), versus the observed data. Both coupled models capture well the interannual variability of the dry-season production, including the large negative anomalies accompanying the 1982–83 and 1997–98 El Niño events. We also examined the relative operating characteristics (ROC) curve (Swets 1973; Mason and Graham 1999) in order to assess their forecasting capabilities for the above- or below-normal rice production within a probabilistic context (Fig. 9).
The areas beneath the ROC curve for forecasting the below- (above-) normal rice production with the OND precipitation anomalies of CFS and ECHAM-MOM are 0.81 (0.84) and 0.82 (0.75), respectively, substantially exceeding the climatological expectation of 0.5. Both coupled GCMs show good ability in predicting above- or below-normal national rice production in the dry season.

FIG. 7. Cross-validated correlation skills of dry-season all-ecosystem rice production, based on the predictors given in the legend. The vertical line indicates the start of the rice production season in January. Each point represents the skill value of forecasts made in that month. See text for details.

FIG. 8. Dry-season detrended observed all-ecosystem national rice production (blue), together with GCM-based hindcast values from the CFS (red with dots) and ECHAM-MOM (green with dots) GCMs, initialized on the previous 1 Jun.
We conducted cross-validated CCA using the ensemble-mean precipitation anomalies over the Philippines in OND from 1982 to 2007 predicted by ECHAM-MOM, which was initiated on 1 June, as the predictors. Similar results were obtained using the CFS.

For both regional irrigated and rain-fed rice production (therefore, for the entire ecosystem as well), statistically significant ($p < 0.05$) forecast skill is limited to several regions in the central Philippines (regions VI, VII, and VIII for irrigated systems and regions IV-b, V, VI, and VII for rain-fed systems) as well as regions XII and ARMM (Fig. 3b) in the southern Philippines (Mindanao) (Fig. 10a). A fairly similar pattern of correlation skill was obtained at the provincial level (Fig. 10b). A detailed comparison of the predictive skill at the regional and provincial levels is unfortunately difficult because of the limited availability of provincial data. Overall, the predictive skill at regional and provincial levels are lower than those at the national level.

c. Rainy-season predictability (July–December)

1) RELATIONSHIP BETWEEN RICE PRODUCTION AND RAINFALL

In contrast to the dry season, rainy-season rice yield and area harvested correlate with rainfall in a complex manner (Fig. 11). The national area harvested of the irrigated rice system correlates quite highly with the SAI
of $S$ from around SON of year($-1$) to MJJ of year(0) (Fig. 11f); thus, more rainfall during the previous season results in an increase in the irrigated area harvested for the following rainy season. At the regional level (Fig. 11; pink curves), positive correlations of rainy-season irrigated area harvested with rainfall during the previous season were also found in most regions, although the correlations are often weak (Fig. 11f). Note that irrigation systems in the Philippines are mostly run-of-the-river systems, and, therefore, the water supply buffer from reservoirs, the river system, and groundwater aquifers from the preceding season would tend to enhance production in irrigated areas (Ines et al. 2002, 2006; Ongkingco et al. 1982).

The above results suggest national-scale climatic impacts, possibly caused by ENSO, on the rainy-season irrigated area harvested during the period. On the contrary, the rain-fed area harvested has a positive but weaker correlation with the rainfall during the previous season except for the significant peak around MJJ (Fig. 11i).

With regard to the national yield, positive correlations of the irrigated yield with the SAI (Fig. 11e) are found from MJJ to JAS of year(0), which rapidly turns into significant negative correlations by SON of year(0). The rain-fed yield correlation (Fig. 11h) has a sharp peak in JAS of year(0), which also turns into negative correlations by the end of the year. At the regional level, both irrigated and rain-fed yields in most regions have insignificant positive correlations (say, $r \approx -0.2-0.3$) around JJA at the 95% confidence level. However, only yields of a spatially confined region, namely the irrigated yield of regions III, IV-a, and V (Fig. 12a) and the rain-fed yield of region III, have significant negative correlations ($p < 0.05$) with the SAI in OND. Since all
regions whose yields are negatively correlated with the SAI are located in the north-central Philippines, such spatial correlation patterns may result from some climatic impacts affecting only the northern Philippines during the period, such as tropical cyclones causing flood and wind damage to rice crops.

2) IMPACT OF TROPICAL CYCLONES

Figure 11 indicates negative impacts of rainfall on the rainy-season yields during the late rainy season. Since the Philippines is one of the countries that is most vulnerable to tropical cyclones during the rainy season, the impacts of tropical cyclones on the rainy-season yields were examined using the ACE (section 4d). Interannual variability of July–December ACE exhibits statistically significant ($p < 0.05$) negative correlations with irrigated yields of regions IV-a, IV-b, and V (Fig. 12b), and the rain-fed yields of regions IV-a and V (not shown). Weak negative correlations were also found in both irrigated and rain-fed systems only in the northern part of the Philippines (CAR and regions II and III), though they are not statistically significant at the 95% confidence level.

Differences in the impacts of tropical cyclones occurring during JAS versus OND were also examined: OND is normally the mature stage, when grains are already ripe for harvest, whereas JAS is the early stage of the growing season. The ACE in OND has negative correlations ($p < 0.05$) with the irrigated yields of CAR and regions III, IV-a, IV-b, and V as well as the rain-fed yields of regions III, IV-b, and V, whereas no significant correlations with the ACE in JAS were found. Thus, tropical cyclones are found to mainly impact rainy-season rice yields during OND. It is also interesting to note that SAI of $S$ in OND and ACE in OND have significant negative correlations with the irrigated and rain-fed yields only around the central Philippines, although their detailed patterns are different.

3) PREDICTABILITY OF RAINY-SEASON RICE PRODUCTION

(i) National level

As shown in sections 5c(1) and 5c(2), we found positive correlations between the rainy-season area harvested (especially in irrigated systems in most regions across the country) and the rainfall during the previous season. Rainy-season yields are negatively correlated with the SAI of rainfall and tropical cyclone ACE mainly in OND, and especially in irrigated systems in the north-central Philippines, while positive correlations with the SAI of rainfall in JAS were observed in rain-fed systems.

Following the same procedure of regression model building used in section 5b(2), we examined the predictive
skills of WWV and ZW, in addition to the Niño-3.4 index (Fig. 13). We did not attempt to use the GCM hindcasts of precipitation because of the complex relationship between rice and rainfall. The predictive skills of WWV and ZW are relatively constant at around 0.5–0.6 throughout the first half of the calendar year, with a peak at the beginning of March (namely for WWV and ZW in DJF). Figure 14 shows the hindcast anomalies of rainy-season all-ecosystem national production versus the observed, using WWV and ZW in DJF as predictors. The interannual variability is well captured using these DJF predictors, which precede the sowing season for rainy-season production, which generally takes place around April–May.

(ii) Regional and provincial level

The predictive skills of WWV and ZW in DJF for rainy-season rice production at regional and provincial levels were also investigated using MLR for each region and province individually (Fig. 15). For both irrigated and rain-fed rice production, most regions in Luzon have significant predictive skills, while most of the other regions do not. Regional yields in the rainy season show a similar spatial pattern of predictive skills, whereas the harvested area does not (not shown). Predictive skills in Luzon-average rice production are also plotted in Fig. 13, which demonstrate that Luzon rainy-season rice production is generally more skillful than that for the Philippines as a whole, with a peak of about $r = 0.7$ in March. Figure 16 shows an ROC diagram for rainy-season Luzon rice production. The area beneath the ROC curve for predicting the below- (above-) normal rice production in Luzon with WWV and ZW in DJF is 0.74 (0.72), indicating the good ability to predict above- (below-) normal rainy-season Luzon rice production from the previous March.

6. Summary and discussion

The aim of this study was to assess the predictive skills of state-of-the-art seasonal climate forecasts, such as coupled GCMs, in the prediction of rice production in the Philippines, in order to explore their potential for decision making at different levels ranging from national policy makers to local farmers. To this end, cross-validated predictive skills for rice production were calculated at national, regional, and provincial levels using GCM hindcasts of precipitation and indices of observed antecedent equatorial SST, warm water volume, and zonal winds.
The spatial coherence of seasonal anomalies of observed station rainfall in the Philippines was first investigated in order to assess the potential predictability of rainfall at local scales. This analysis demonstrated a clear contrast in the rainfall predictability between the dry and rainy seasons: in the Philippines, seasonal anomalies of dry-season precipitation are found to be highly spatially coherent between stations (potentially predictable) (Fig. 4), and ENSO is strongly anticorrelated with seasonal rainfall attributes (Fig. 5). A lag correlation analysis (Fig. 6) revealed a strong dependence of the dry-season yields, areas harvested, and rice production, on rainfall toward the end of rainy season and the beginning of the dry season, namely the sowing season for dry-season rice crop around October. At that time the correlation with rainfall reaches a maximum of around 0.8 at the national level, obtained by summing up regional production figures. Weaker but common responses to climatic signals in dry-season rice production at the regional level (Fig. 10) reinforce each other at the national level, with the result that summing up of regional production cancels other spatially random variabilities of rice production. Weak correlations between dry-season rice production at provincial and regional level and rainfall might suggest that rice production at those levels is not well predicted even when precipitation is predictable at the local levels as indicated in section 5a, possibly due to failures related to removing nonclimatic factors using the low-pass filter, and therefore the importance of consideration of interannual socioeconomic influences at seasonal to interannual frequencies. If that is the case, skillful forecasting systems of rice production at spatially finer scales might need to reproduce such seasonal to interannual variability of rice production due to nonclimatic factors, for instance, by integrating economic and/or crop models.

This study found high predictive skill using CFS, ECHAM-MOM coupled GCM forecasts of Philippines precipitation, and antecedent observed WWV and ZW indices in the dry-season rice production, sufficient to forecast more than half of the total variances of the dry-season rice production in the Philippines with about a half-year lead time from the beginning of the harvest (Fig. 7). The performance levels of the GCM-based and purely empirical models are often fairly comparable, although coupled GCMs, and the CFS model in particular, deliver the highest skill values at long leads. Thus, the semiempirical models that include GCM precipitation forecasts do add value in some cases over the purely empirical models. While future work is required to investigate the GCM-derived results in detail, this added value can be expected to increase in the future as GCM seasonal forecast systems improve in quality. The high predictive skills of climate forecasts encourage
development of a forecasting system for decision making related to food security by the Philippine government, the only agency authorized to import rice (Dawe et al. 2006). This will ensure food security by better controlling the amount of imported rice.

The results for the rainy-season rice production, on the contrary, are more complex. Relations of the areas harvested with rainfalls differ from those of the yields: while the areas harvested in most regions have positive correlations with the rainfall in the precedent dry season, rainfalls during the latter periods of rainy seasons negatively affect the rainy-season yields of the central-north Philippines (Fig. 11). The ACE analysis showed a strong impact of tropical cyclone activity on rainy-season yields in the central to northern Philippines (Fig. 12b). It is interesting to note that the correlation patterns of rainfall and ACE in OND with yields are somewhat different. The impacts of tropical cyclones on rice production may be due to rainfall, flooding, or strong winds, or some combination thereof; since these impacts are still not well understood, despite a handful of previous studies (e.g., Iizumi et al. 2008; Masutomi et al. 2010), detailed analysis is encouraged as a topic for future research.

Such complexity of relationships between rice and meteorological conditions during the rainy season makes it difficult to select appropriate predictors. In this study, WWV and ZW were selected for assessment of the predictive skills. The contrast in patterns of predictive skills between the northern Philippines and the other regions is remarkable. Regions with high predictive skill in rice production are mostly confined to the central to northern Luzon, which corresponds well to the pattern

**Fig. 15.** Cross-validated correlation skills for rainy-season all-ecosystem rice production at the (a) regional and (b) provincial levels. The WWV and ZW in the previous DJF were used as predictors.

**Fig. 16.** ROC diagram for forecasts of the above- or below-normal tercile categories of rainy-season all-ecosystem Luzon rice production, based on WWV and ZW in the previous DJF.
of predictive skills in yields (not shown). Note, however, that this pattern is different from correlation patterns of the rainy-season yields with rainfall and tropical cyclones (Fig. 12). Careful analysis, including the possibility that we might miss some meteorological factors influencing the rainy-season yields, is needed for investigation of this difference. Some of the candidates for such missing factors might be other meteorological elements such as temperature and solar radiation variability (e.g., Iizumi et al. 2010), as well as the timing of the onset and/or the strength of the monsoon, considering that much of the Philippines is located within the western North Pacific boreal summer monsoon region, which is part of the broad-scale Asian–Pacific southwest monsoon system (e.g., Wu and Wang 2000; Wang et al. 2001; Wang and Ho 2002).

This paper has shown high potential of crop forecasting based solely on climate forecasts in the Philippines, but has also shown limitations at regional and provincial levels. Some previous studies have shown the potential of crop simulation models driven by seasonal rainfall forecasts for crop yields (e.g., Hansen et al. 2004; Hansen and Indeje 2004; Mishra et al. 2008), whereas it has also been found that crop simulation models do not predict improvements of crop yields where seasonal climate forecast skills are low (e.g., Semenov and Doblas-Reyes 2007). The positive findings presented here for the Philippines based on empirical and semiempirical models motivate future work to assess the performance of crop simulation models driven by GCM seasonal climate forecasts for the prediction of the Philippine rice production at regional and provincial levels.

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