Predictability of Rice Production in the Philippines with Seasonal Climate Forecasts

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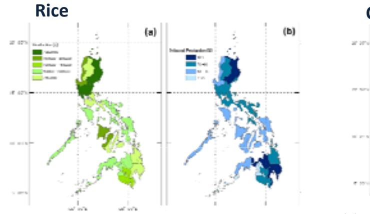
1. Introduction

Rice is the most important crop for the people of the Philippines. Because the fluctuation in domestic rice production has direct impacts on food security, especially for the poorest people, the stabilization of domestic rice production is a critical concern for the Philippines in terms of its food security. Rice is known as one of the most highly susceptible cereal crops to climate variability. ENSO is the most influential factor on the Philippine climate with measurable impacts on the agriculture. The previous studies demonstrated large impacts of ENSO on the Philippine rice production, and potential of climate information for the prediction (e.g. Roberts et al. 2009). Development of forecasting systems for rice production at different levels from the national government to local farmers based on climate information is an important issue for the Philippines.

Here, we have conducted the assessment of predictive skills of one uncoupled general circulation model (GCM) and two coupled GCMs, as well as Niño 3.4 SSTAs and the volume of water warmer than 20°C (WWV) in the equatorial Pacific Ocean (5°N-5°S, 120°E to 80°W) at the national, regional, and the provincial level.

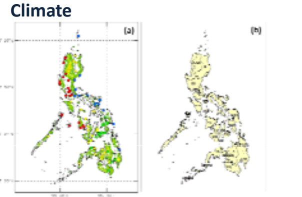
2. Study Region

Rice



(a) Annual rice production and (b) percentages of irrigated production in 2007.

Climate



(a) 77 stations used in the analysis (red, blue, yellow, and green dots represent Type I, II, III, and IV climate defined by PAGASA), and (b) Region names in the Philippines respectively.

3. Methodology

Detrending and Normalization of Rice Data

Rice production is influenced by non-climatic factors such as change in technology, land use from rainfed system to irrigation system, soil quality and market. Here, we assumed that such non-climate factors influence rice production at lower frequencies than climate factors and can be removed with a low pass spectral smoothing filter. We used the Butterworth's low-pass filter with 10 year cut off period to detrend the rice data. The cut off period was chosen based on other similar published and non-published researches (e.g. Baigorria et al. 2008). Residuals of rice data were calculated as a deviation from the trend divided by the trend [(observed value - trend)/trend]. The residuals of rice data often depart from normality. Considering some statistical methods used in the paper assume normality of rice data, a Box–Cox transform (Box and Cox 1964) was applied to the residuals of rice data to correct the departures from normality before analysis.

Spatial Coherence

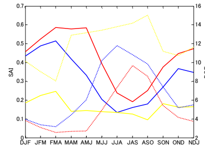
Assuming that inter-annual rainfall variability caused by large scale climate forcing such as ENSO are relatively spatially uniform (Haylock and McBride 2001; Moron et al. 2006; Moron et al. 2007), spatial coherence of rainfall carries information on predictability of seasonal rainfall; higher spatial coherence denotes higher predictability. Two different measures, inter-annual variance of standard anomaly index (SAI; Katz and Glantz 1986) and degrees of freedom (DOF; Fraedrich et al. 1995) were used. The DOF estimates the number of independent variables in a dataset in terms of empirical orthogonal functions (EOFs); higher (lower) values represent lower (higher) spatial coherence. Inter-annual variance of SAI, var (SAI) is alternative of spatial coherence to the DOF. For example, if seasonal rainfalls between all stations are perfectly correlated, var (SAI) is 1; if seasonal rainfalls of all stations are independent, var (SAI) = 1/M where M is the number of stations (Katz and Glantz 1986; Moron et al. 2006). The DOF and var (SAI) are consistent estimators of spatial coherence (Moron et al. 2007).

Predictability Analysis

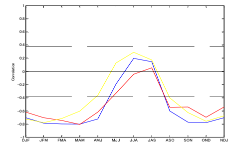
Retrospective predictive skills of the Philippine rice production with climate variables were investigated based on cross validation. Cross validation is a method to estimate actual predictive skills better, by reducing artificial skills resulting from overfitting: forecast models are reconstructed with only a part of the dataset, and then applied to the omitted one. The number of subsets can be all possible combinations of a given number of withdrawn points (e.g. Barnston et al. 1993). In this paper, leave-five-out cross validations was conducted. Namely, 5 year samples were withheld for developing a regression equation with those techniques, and the forecast was made only for the central year of the withheld years. Climate variables selected as predictors here include Niño-3.4 SSTAs, WWV plus zonal wind anomaly over the west equatorial Pacific (2ºS-2ºN, 180ºE-220ºE), and predicted ensemble mean total precipitation over the Philippines (0ºN -25ºN, 110ºE -130ºE) from 3 GCM ensembles, ECHAM-CA, ECHAM-MOM, and CFS. Cross validations with three different statistical techniques, Multiple liner regression (MLR), Principal Component Regression (PCR), and Canonical Correlation Analysis (CCA) were performed.

4. Result

Spatial Coherence & Potential Predictability of Rainfall

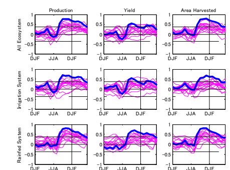


SAI (solid line) and DOF(dotted line) for seasonal amount (blue), occurrence of rainfall (red), and mean intensity of rainy days(yellow) of the 77 station network (1977-2004).

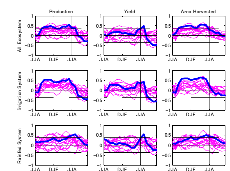


Correlation between Nino 3.4 SSTAs and SAI for seasonal amount(blue line), occurrence of rainfall(red line), and mean intensity (yellow line) of rainy days of the 77 station network (1977-2004).

Relationship between rice production and rainfall



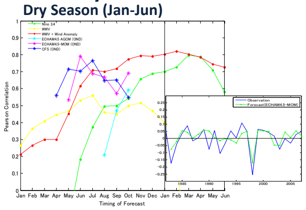
Lag correlation of dry-season rice production, yield, and area harvested of the Philippines(blue) and region(red), with SAI of seasonal amount from DJF of year(-1) to MJJ(year(0)).



Same as the left figure except for rainy-season rice production, yield, and area harvest from JJA of year (-1) to DJF of year (0).

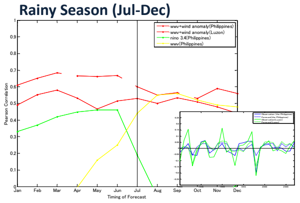
Predictability of National Rice Production

Dry Season (Jan-Jun)



Cross validation correlation skills of dry-season rice production of all ecosystems of the Philippines. Nino 3.4, WWV, and WWV plus zonal wind anomalies over the west equatorial Pacific (1980-2007) were used as predictors of multiple liner regression (MLR). Seasonal precipitation anomalies in OND over 0N-25N, 110E-130E forecasted with ECHAM 4.5(1980-2006), ECHAM4.5-MOM (1982-2007), and NOAA CFS(1981-2007) were used as predictors of principle component regression (PCR).

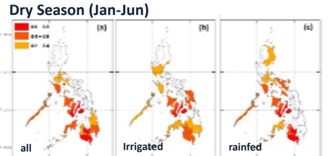
Rainy Season (Jul-Dec)



Cross validation correlation skills in rainy-season rice production of all ecosystem of the Philippines and Luzon. Nino 3.4, wwv, and wwv plus zonal wind anomalies over the west equatorial Pacific (1980-2007) were used as predictors of MLR.

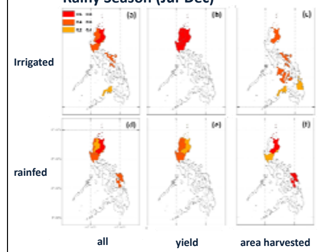
Predictability of Regional Rice Production

Dry Season (Jan-Jun)

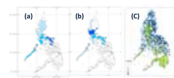


Cross validation correlation skills of dry-season rice production of all ecosystem (a), irrigation system(b), and rainfed system(c) at regional level. Seasonal precipitation anomalies in OND (110E-130E, 0N-25N) forecasted with ECHAM4.5-MOM(1982-2007) on 1st June were used as predictors of CCA.

Rainy Season (Jul-Dec)

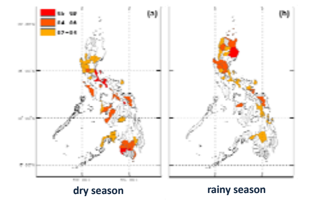


Cross validation correlation skills in rain-season rice production (a), yield (b), and are harvested (c) of the irrigation systems at regional level. WWV plus zonal wind anomalies over the west equatorial Pacific(1980-2007) in DJF were used as predictors of MLR. (d)-(e) are same as (a)– (c) except for rainfed systems.



Correlations between rainy season yields of (a) irrigation systems with SAI in OND of year(0) . (b) is same as (a) except for ACE in JASOND. (c) shows observed points of tropical cyclones by category in JASOND within 100 km of the coasts of the Philippines from 1977 to 2007.

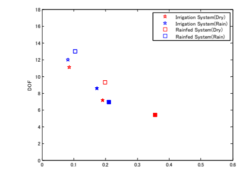
Predictability of Provincial Rice Production



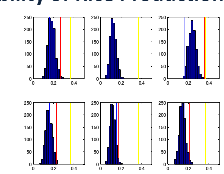
(a) Cross validation correlation skills of dry-season rice production of all ecosystem at provincial level. Seasonal precipitation anomalies in OND (110E-130E, 0N-25N) forecasted with ECHAM4.5-MOM(1982-2007) on 1st June were used as predictors of CCA.

(b) Cross validation correlation skills in rain-season rice production at provincial level. WWV plus zonal wind anomalies over the west equatorial Pacific(1980-2007) in DJF were used as predictors of MLR.

Spatial Coherence and Potential Predictability of Rice Production



var (SAI) and DOF of irrigated and rainfed productions in dry season(red) and rainy season (blue) of 16 regions(filled marks) and 54 provincess(open marks), 1977 to 2007.



Histograms of var (SAI) of dry season rice production of (a) all ecosystems, (b) irrigation systems, and (c) rainfed systems of 16 provinces randomly selected from 54 provinces (blue bars). (d)–(f) are same as (a)-(c) respectively except for rainy season. Var(SAI) of regional rice production(red) seasonal amount in JAS (blue) and OND(yellow) are also shown here.

5. Concluding Remark

- Spatial Coherence Analysis clearly shows high predictability of dry season rainfall and low predictability of rainy season one. It also shows higher predictability of dry season rice production of rainfed system.
- At the national level, dry season rice production of both irrigation and rainfed systems largely depend on rainfall in OND of the year before the harvest The two coupled GCMs have high predictive skills (r~0.8) for the national dry-season rice production with lead time of half a year (six months before the beginning of the harvest). WWV plus zonal wind anomalies over an equatorial west Pacific also has similar predictive skills to those of these coupled GCMs. The uncoupled GCM only has similar predictive skills to Niño 3.4 SSTAs with shorter lead time by three to four months than the coupled GCMs.
-Predictive skills at the regional level are generally lower than that at the national level. Most regions with high predictive skills are located in southwest of Mindanao and the central Philippines.
- Rainy season rice production at the national level has correlations with rainfall in complex manners. The national area harvest positively correlates with rainfall during the precedent dry season. The national yield in rainy season has positive and negative correlations with rainfall in JAS and in OND respectively.
- WWV plus zonal wind anomalies over the equatorial west Pacific have high predictive skills(r~0.7) in the natioanl rainy-season rice production with a few months lead time from the beginning of the harvest.
- Only regions in Luzon showed high predictability while the other regions do not. Such spatial difference in predictability of rainy season rice production might be due to difference in impacts of climate such as flood and tropical cyclones on the yield.