Short-Term Climate Predictability of Summer Rainfall for Taiwan

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1. Introduction

Variability of summer rainfall in Taiwan has received much attention because of its great impact on the economy of Taiwan. Droughts have been recurrent and severe problems to this island, often resulting in low crop yields, insufficient electricity production and shortage of water supplies (Wu, 1992). The wet spells in some years caused equally serious problems. Therefore, seasonal prediction and predictability studies for summer rainfall have been recognized as the important elements for strategic water resources planing and management.

The Mei-Yu season in Taiwan occurs from May to June and is characterized by quasi-stationary fronts. Based on the antecedent Pacific sea surface temperature (SST) using a linear statistical model, Chu (1998) showed that the predictability of Mei-Yu rainfall is moderate. From July to October, rainfall is primarily produced by tropical cyclones and local thunderstorms. This study focuses on the latter period, since rainfall predictability in this extended summer season (JASO) has not been well studied. This is the time when typhoon activity is most vigorous.

Wu (1992) showed that summer rainfall in Taiwan is closely related to the activity of the western Pacific subtropical high and the previous and concurrent SST in the adjacent ocean basin and the eastern equatorial Pacific Ocean. Huang and Wu (1989) studied relationships between El Niño – Southern Oscillation (ENSO) events and summer rainfall in southern China and found rainfall tends to increase in the year following an ENSO event, suggesting that SST in preceding seasons provides potential for a long-lead prediction of summer rainfall. The purpose of this study is to test the impact of planetary-scale surface boundary conditions on seasonal rainfall predictability in Taiwan. A linear modeling technique called the canonical correlation analysis and a nonlinear approach called the neural network are employed to address the predictability problems.

2. Method and Data

2.1 Linear and Nonlinear Models

Canonical correlation analysis (CCA) is selected as the tool for this study. CCA is a coupled linear statistical model which attempts to determine the optimum correlation between the predictor and predictand patterns (e.g., Barnett and Preisendorfer, 1987; Chu and He, 1994; Barnston and He, 1996; and Yu, Chu, and Schroeder, 1997). Neural network (NN) is an artificial intelligent system which imitates some function of human brain. This technique is recently recognized as a powerful statistical approach to forecast climate variations (e.g., Hastenrath et al., 1995; Navone and Ceccatto, 1994). We use the fully connected three-layer, feed-forward system, which consists of three layers: the input, hidden, and output layers.

2.2 Data and Data processing

The data field to be predicted is the aggregated precipitation in 16 stations spread over Taiwan from January 1956 to October 1997. This dataset is derived from monthly rainfall records kindly provided to us by G.-H. Chen of the Central Weather Bureau. The percentage of rainfall in these four summer months (JASO) to the annual totals varies from 30% in northwest to 60% in southeast Taiwan. The predictor data field encompasses the Pacific and the Indian Oceans and the South China Sea. SST data in these three ocean basins are derived from the NCEP/NCAR reanalysis product spanning the period from 1955 to 1997. The resolution of SST for the Pacific and Indian Oceans is 10° by 10° but is 2° by 2° for the South China Sea.

Prior to applying CCA and NN, the predictor and predictand fields are standardized and preorthogonalized using EOF for rainfall and empirical EOF analysis (EEOF) for SST. By applying preprocessing procedure EEOF, large special points for SST field can be transformed to a modest number of EEOF modes and the small noise involved in SST and rainfall fields is filtered out. In addition to the spatial compression, the EEOF analysis enables us to capture stationary as well as propagating features of the SST. This is achieved by stacking the four temporal series of the SST field into a big matrix so that the evolution of SST spatial pattern over a one year period is preserved.

2.3 Mode Selection and Procedure

There is no universal agreement upon the procedure for determining how many EEOF modes should be retained. In this study, the number of modes to be retained in the analysis is determined using forecast skill sensitivity tests. This is performed by cross-validation with varying number of retained predictor and predictand EOF modes. Results of the test reveal best prediction skills when four modes of the predictor field and eight modes of the predictand field are retained.

The prediction skill for different lead time from one to 11 months is calculated. The lead time is defined as the number of the last month between the predictor data and the first month of predictand season (i.e., JASO).

3. Result and Discussion

3.1 The origin of prediction skills

In the following, we will present the canonical loading maps between the summer rainfall and EEOF-derived SST fields over three ocean basins with one month lead time. The canonical predictor map (i.e., g map) of the first CCA mode is presented in Fig. 1. A strong signal along the equatorial eastern Pacific starts from JJA of the previous year and progresses to MAM, just prior to the summer season. However, this signal gradually weakens throughout MAM. Fig. 1 also shows the importance of the monsoonal western Pacific and the midlatitude central North Pacific.

The extent to which the rainfall field is predictable from the large-scale SST pattern is seen in Fig. 2 (i.e., hn map). For both the equatorial western and eastern Pacific, anomalously warm SSTs are associated with wet conditions over northern and eastern Taiwan. In particular, high correlations (>0.5) are found for Ilan

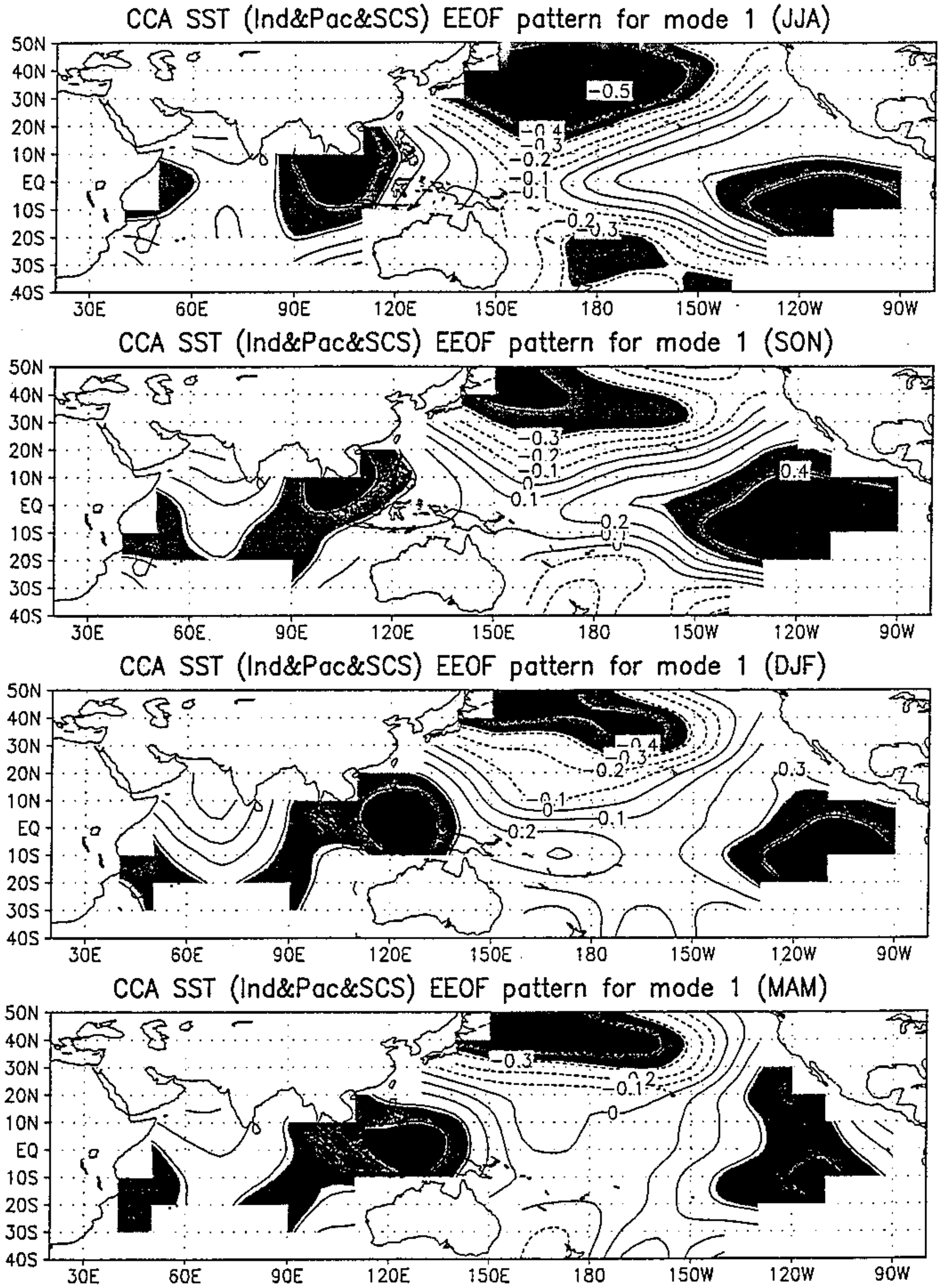

Fig. 1. Canonical predictor map of the first CCA mode of June/July/August (JJA) through March/April/May (MAM) sea surface temperatures and July/August/September/October (JASO) rainfall in Taiwan. Shading denotes regions where correlations are locally significant at the 95% level.

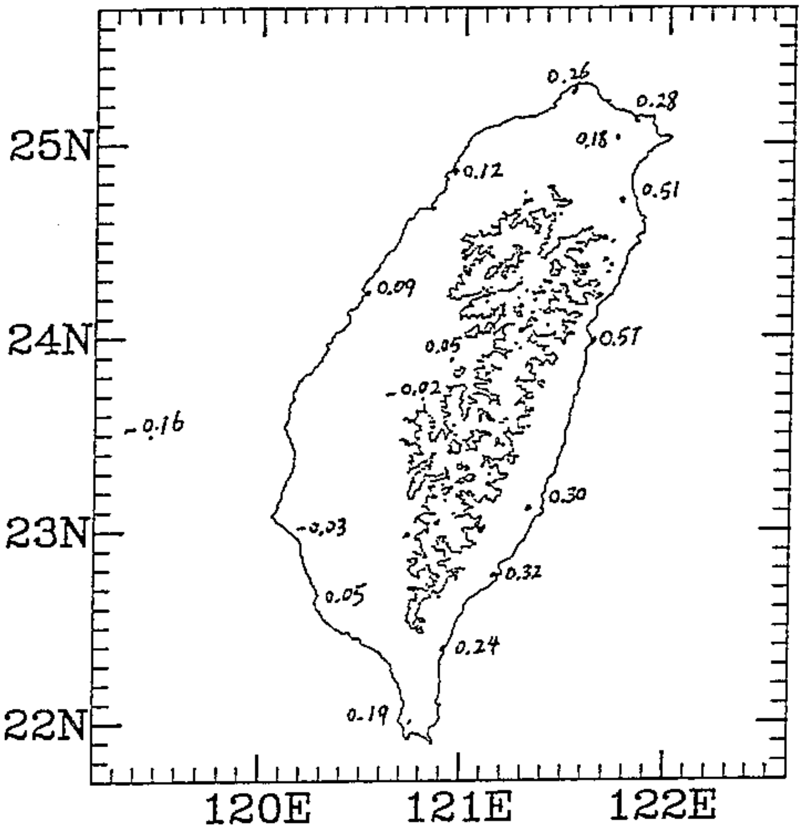

Fig. 2. Canonical predictand map for the first CCA mode for JASO rainfall.

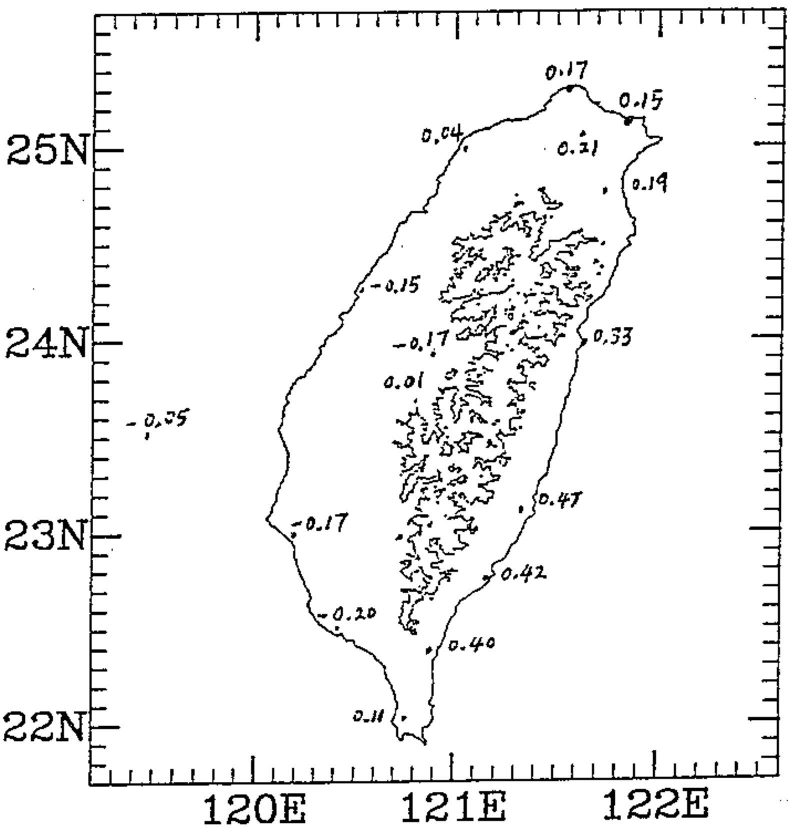

Fig. 3. Canonical predictand map for the second CCA mode for JASO rainfall.

and Hualien. The correlations are very low for the western plain. Thus, this mode seems to be a major contributor to the predictability of JASO rainfall for eastern and northern Taiwan.

For the second CCA mode, the source of predictability is mainly found over the central North Pacific (not shown). For the predictand spatial pattern (Fig. 3), a large correlation (>0.30) with SST is found over the eastern side of the island, from Hualien, Chengkung, Taitung to Tawu. Like the first CCA mode (Fig. 2), the predictability for the western plain is rather low.

3.2 Spatial distribution of the cross-validation forecast skill

To provide a measure of the overall forecast skill, cross-validation correlation coefficients between the observation and prediction for 42 years are calculated.

The distribution of prediction skills over 16 stations in Taiwan using SST from three ocean basins for 1 month lead is shown in Fig. 4. Modest to high skills (0.2 to 0.49) are found on the east coast of the island, with a significant skill score for Ilan (0.49) and Hualien (0.35). Consistent with the canonical predictand maps, poor forecast skill is expected in the western plain (Fig. 4). Unlike the west coast, summer rainfall in Penghu is somewhat predictable (correlation being 0.37).

3.3 Neural Network Prediction

A nonlinear model is currently under construction and the prediction skill for 1 month lead using SST from three ocean basins will be calculated and compared with CCA prediction experiments.

4. Summary

The statistical short-term climate predictive skills for summer rainfall in Taiwan are assessed using both the CCA and artificial neural network models in a cross-validation manner. SSTs from three ocean basins in 4 consecutive 3-month periods are used as the only predictor variable. Thus, the goal is to assess the extent to which summer rainfall is predictable from the slowly varying, antecedent surface boundary conditions. Predictability with up to 11 month lead and the origin of the predictability from three ocean basins is estimated. As expected, the prediction skill drops with lead time increasing and the highest skill is found in short lead times.

It is found that the first CCA mode provides the most skill to summer rainfall for eastern and northern Taiwan. Particularly noteworthy is the large loading in the western Pacific warm pool region in the canonical predictor map (SST). This anomalous pattern would affect atmospheric heating distribution and thus tropical convection. Because of its proximity to east Asia, summer rainfall in Taiwan is likely to be modulated by the anomalous SST-induced convection in the tropical western Pacific. Soman and Slingo (1997) also emphasized the importance of the anomalous SST in the preceding spring in the tropical western Pacific in affecting summer circulation over Asia. The second CCA mode contributes most to the predictability for the eastern and southeastern Taiwan.

Cross-validation of CCA forecasts at one month lead reveals that rainfall in the eastern and northern Taiwan is more predictable than that in the west plain. It is suspected that summer rainfall variability on the east coast is directly related to the SST fluctuations in the Pacific Ocean since most of the skill comes from this basin. In a separate experiment, predictability based on the Indian Ocean alone is found not to be important. Blocked by the high Central Mountain Range, the Pacific SST seems to exert a minimum influence on summer rainfall activity in the western plain.

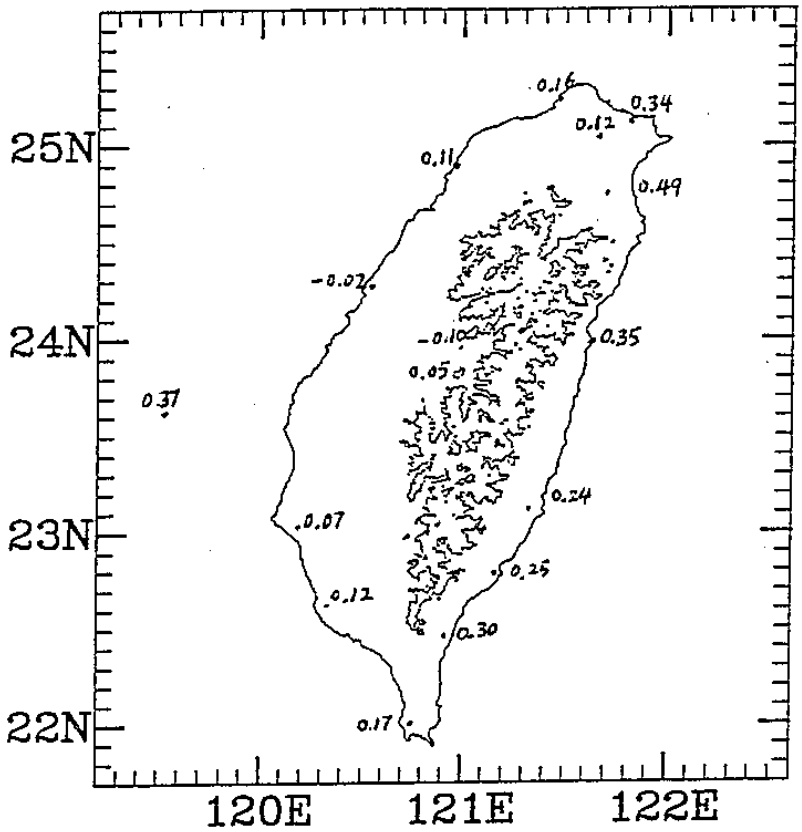

Fig. 4. Cross-validated hindcast correlation skill between observed and predicted JASO rainfall at one month lead using CCA. All three ocean basins (the Pacific and Indian Oceans as well as the South China Sea) are included.

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