Identification of Suitable predictors to Develop a Seasonal Forecasting Model for District Rainfall for the onset of Maha Agricultural Season using Climate Predictability Tool (CPT)

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ABSTRACT

This study is focused upon identification of best predictor to predict the September monthly rainfall in the middle of August for Sri Lanka. Seasonal prediction of probability of receiving September rainfall in advance would help to prevent crop damages and losses in paddy cultivation as well as other short term crop cultivations and also it would help in better managements of water resources in the area because the onset of the main agricultural season " Maha" starts in the month of September.

A variety of challenges have been encountered in the process of producing and providing seasonal prediction to users. One of the major challenges is the accuracy of the prediction. It is important to find out the best predictors that can be used for seasonal prediction. Composite analysis technique was carried out for the large-scale atmospheric variables for anomalous positive rainfall years as well as anomalous negative rainfall years to identify best predictors as well as best domains that could have a significant impact on September rainfall over Sri Lanka.

Statistical downscaling of Climate Forecasting System (CFS) predictions was carried out using Climate Predictability Tool (CPT). For downscaling, Zonal wind and Meridional wind at different atmospheric levels as well as sea surface temperature (SST) from CFS were used as predictors with the hindcast data spanning a period of 30 years from 1982 to 2012 with initial conditions from the 1st week of the August.
Results indicate that SST over the Pacific Ocean (15^{0}N-15^{0}S latitude and 160°E−230°W longitude) has highest overall predictability with good skill for September Forecast. Predictability skill of the zonal wind and meridional wind components were poor for September forecast.

Key words: Canonical Correlation Analysis (CCA). Downscaling, Climate Predictability Tool (CPT), Zonal wind, Meridional wind, Sea Surface Temperature (SST), Climate Forecasting System (CFS), Hindcast data.

1 Introduction

Seasonal predictions provide useful information in planning various activities that depend on climate information and products. Seasonal predictions commonly tackled either by experimenting with sophisticated General Circulation Models (GCMs) (Palmer and Anderson, 1994) or statistical models based on correlations between predictands (the weather variables to be predicted) and predictors (the weather variables used to produce the prediction) (Vautard, R, 1998). Predicting the future is never easy but over the last few decades, climatologists have improved on this with regards to the climate (Palmer and Anderson, 1994). Due to the climate drift and other problems intrinsic to GCMs (Tracton et al. 1989; Brankovic et al. 1990; De´que´ 1991) in predicting long-term weather behavior it is not surprising that the seasonal skill of GCMs may not necessarily be the best (Van den Dool 1994).

It is an important task to predict the onset of rainy season for different key sectors in Sri Lanka for economic development. Out of all the sectors, agriculture and food security play an important role, because agriculture is highly sensitive to fluctuations in weather and climate. It is a requirement from the Agriculture Department to provide onsets of rainy season with some accuracy. Generally the annual weather pattern over Sri Lanka is Bi-Model and two peaks are related to the months of April and November. But the rainfall begins to increase during mid-March and mid-September. Accordingly, farmers are used to start their agriculture practices. The economic importance of predicting September rainfall in advance is huge because major agricultural season called “Maha” starts with the onset of September Rainfall . Nearly 72% of paddy production, the staple food in Sri Lanka, is grown during the Maha season (September to March) in dry areas where water resources are stressed (De Silva et al. 2007).

GCM products generally provide seasonal forecasts that could be useful for large scale regions; however, because of their coarse resolution of several hundred kilometers, they may have limited practicality for small-scale local administrative areas within the region. However, GCMs can provide skillful seasonal forecasts of mean circulation, particularly in the tropics, and such information may be used to forecast rainfall at a localized area. It has been shown that forecasting skills for rainfall at a local area can be further improved using a statistical downscaling of dynamically forecast atmospheric variables such as lower trophospheric zonal wind, meridional wind and Sea Surface Temperatures (SST). Objective of this study is to find the best predictor to predict rainfall of the month of September. Forecasting September rainfall in one month ahead will help to mitigate the crop damage due to extreme rainfall (flood and drought).It will also help the farmers to select appropriate crop varieties for the next season

A common approach used in seasonal forecasting is to estimate the likelihoods of a small number of mutually exclusive events. Typically three equi-probable categories “below normal,” “near normal,” and “above normal” are considered. Forecast uncertainty is characterized by the discrete probability distribution of the three outcomes. This forecast format is motivated by the simplicity of the forecast presentation and is used by many operational centers that make seasonal forecast (Viatcheslav and Francis, 2003).

This study is focused on finding a predictor to produce probabilistic rainfall forecast for 25 districts in Sri Lanka using Climate predictability tool. GCM data provid by Climate Forecasting System (CFS) is used for the CPT as predictors. Predictor selection procedure was carried out using composite analysis technique.

2 Data and Methodology

2.1 The Datasets

Hindcast data from Climate Forecasting System (CFS) model (Saha et al 2010), developed and operated by National Centers for Environmental Prediction (NCEP), USA, were used as inputs (or predictors) for the statistical downscaling models. The Japanese Meteorological Agency’s JRA-55 reanalysis data were used for predictor selection process. The target rainfall (or the predictand) data were provided by the Department of Meteorology (DOM) Sri Lanka. It was taken as actual rainfall data and areal rainfall data from 1961 to 2015 using entire DOM rainfall database.

2.2 Climate Predictability Tool (CPT)

Climate predictability tool (CPT), a statistical downscaling tool, developed by IRI (International Research Institute) is tailored for producing seasonal climate forecasts using model output statistic (MOS) corrections To climate predictions from general circulation model (GCM), or for producing forecasts using fields of sea-surface temperatures.

2.3 Canonical Correlation Analysis (CCA)

For prediction of September rainfall, canonical correlation analysis (CCA) is used, as described in previous studies (Barnett and Preisendorfer 1987; Barnston and Smith 1996; Thiaw et al. 1999). CCA is a multivariate regression that relates patterns in predictor fields (e.g., SST) to patterns in a predictand field (e.g., rainfall). Cross validation (Michaelsen 1987) and retroactive designs are used to minimize inflation of the skill estimates.

2.4 Interactive tool for Analysis of the Climate system

Interactive Tool for Analysis of the Climate System (ITACS) has been used in this study. The ITACS is a web-based application for climatological analysis. The Japan Meteorological Agency (JMA) has developed the ITACS to assist National Meteorological and Hydrological Services (NMHSs) in analyzing the causes of extreme climate events. The ITACS will enable users not only to monitor current climate conditions but also to analyze the characteristics and factors that lie behind such conditions and extreme climatic events. The ITACS equips a variety of statistical analysis tools. So, it is easy for users to perform statistical analysis like composite analysis, linear regression analysis, and correlation analysis on climate systems without complicated programming.

2.5 Identification of positive and negative rainfall years

Observational rainfall data from 1980 to 2014 were divided into 5 categories as extremely below, below normal, normal, above normal and extremely above by comparing the data with 30 year average rainfall data. Main meteorological stations observational data were considered for the analysis and they were plotted according to above categorization. Five positive and five negative rainfall years were identified accordingly (Fig 1and Fig 2).

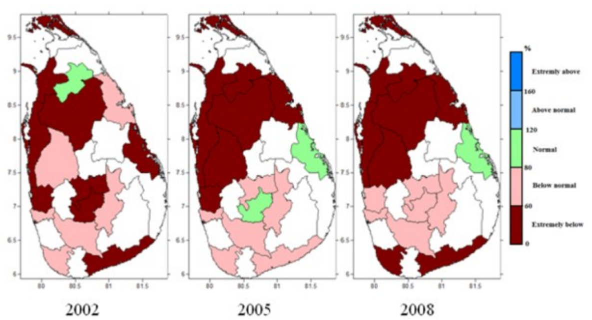

Fig 1: Rainfall maps in negative rainfall years

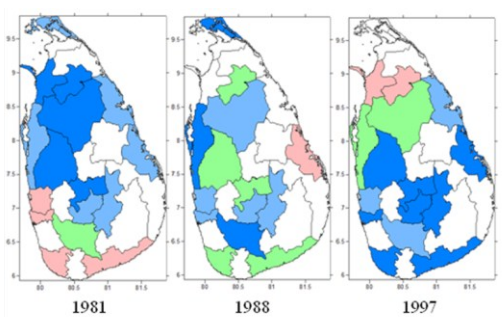

Fig 2: Rainfall maps in positive rainfall years

2.6 Composite analysis technique

Composite analysis technique was carried out for zonal wind at 850 and 500hpa levels and Sea Surface Temperature (SST) for anomalous positive rainfall years as well as anomalous negative rainfall years to identify best predictors as well as best domains which have a significant impact on the monthly rainfall over Sri Lanka. ITACS web-based software was used in the method.

3 Results and Discussion

For the month of September, significantly above normal rainfall was received in years 1981, 1984, 1988, 1997 and 2004 while the rainfall was significantly below normal in the years 1990, 1993, 2002, 2005 and 2008. Composites maps were plotted for SST and winds at different upper levels for the years above normal and below normal. The maps are shown in the figures.

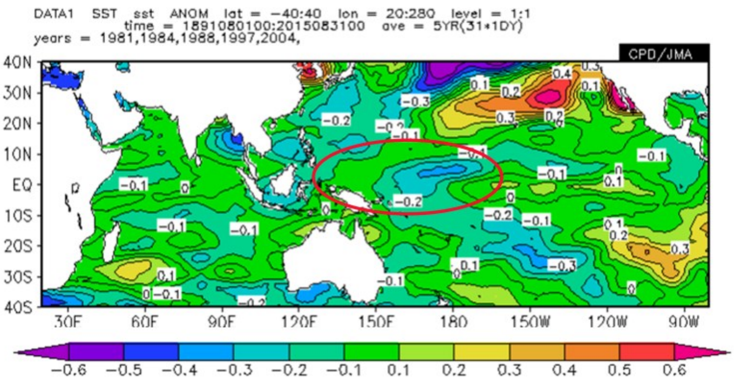

Figure 3: Composite image of SST anomaly during above normal rainfall years for the month of September

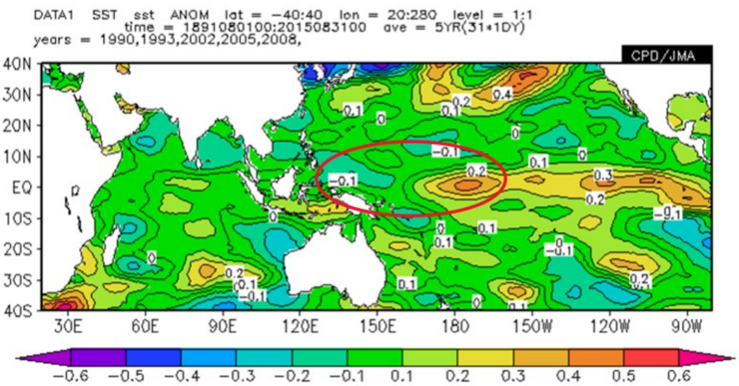

Figure 4: SST anomaly during below normal rainfall years for the month of September

Figures 3 and 4 show the SST composite map for the years above normal and below normal respectively. Figure 3 indicates negative anomalies over the Pacific Ocean. While composite image of the sea surface temperature during below normal rainfall years (Figure 4) indicates positive anomalies over the same region in Pacific Ocean. The region is between 15^0N to 15^0S and 160^0E to 230^0W. Therefore the selected location is a best predictor for predicting the rainfall in September.

Similar analysis was extended to find the suitable area of 500hpa and 850hpa zonal wind. The composite maps for 500hpa and 850hpa are shown in the figures 5 and 6 respectively.

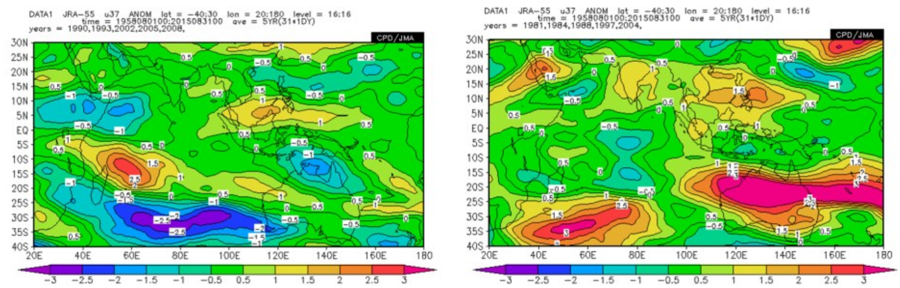

Figure 5: Composite images of zonal wind anomaly at 500hpa during below normal rainfall years (left) and above normal rainfall years (right).

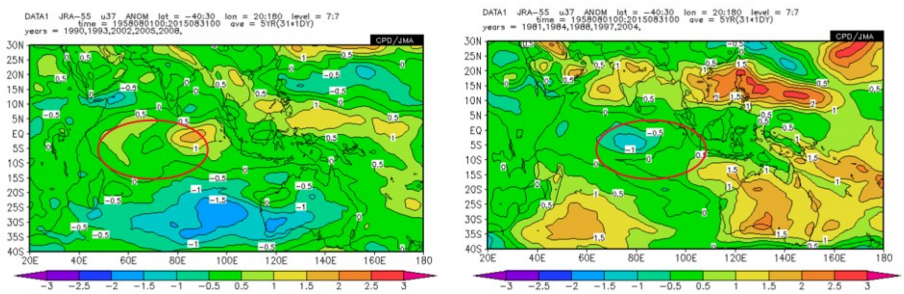

Figure 6: Composite images of zonal wind anomaly at 850hpa during below normal rainfall years (left) and above normal rainfall years (right).

According to the resulted composite anomaly maps, zonal wind at 850hpa level shows positive anomalies during below normal rainfall years and negative anomalies during above normal rainfall years over the Indian Ocean (Figure 6). The region is between 5^0N to 10^0S and 60^0E to 100^0E. 850hpa zonal wind component can also be used as a predictor for the month of September.

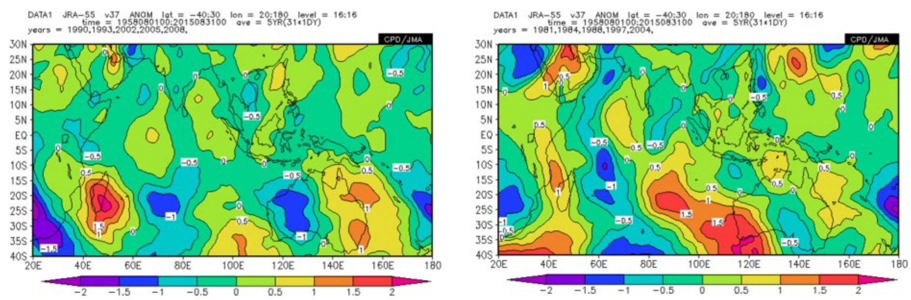

Figure 7: Composite images of meridional wind anomaly at 500hpa during below normal rainfall years (left) and above normal rainfall years (right).

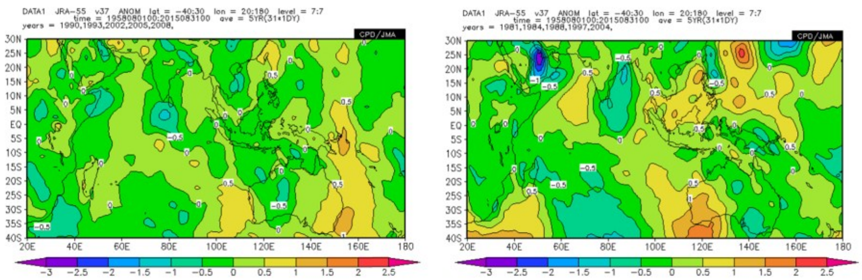

Figure 8: Composite images of meridional wind anomaly at 850hpa during below normal rainfall years (left) and above normal rainfall years (right).

It was not possible to identify a specific region to use as a predictor in meridional wind composite maps.

Statistical monthly rainfall forecast model

To predict monthly rainfall, two regression models are built using cross validated CCA between CFS hindcast data SST over the tropical Pacific Ocean (15^0N-15^0S latitude and 160°E−230°W longitude) and CFS hindcast data of 850 hpa zonal wind over Indian Ocean (5^0N-10^0S latitude and 60°E−100°E longitude) as predictors and areal district rainfall as the predictand for the month of September. The model was built using the Climate Predictability Tool (CPT). The CPT software was developed at the International Research Institute for Climate Prediction (IRI; http://iri.columbia.edu/outreach/software/). Hindcast CFS data spanning a period of 32 years from 1982 to 2014 with initial conditions from the 1st week of the previous months were used in the model.

The predictor and the predictand fields were pre filtered using EOFs, with the number of modes retained determined by maximizing the model's goodness of fit under cross validation, with 5 year withheld at a time.

Forecast Verification

According to the models developed to predict the rainfall of the month of September the results were plotted. Actual rainfall values of the month of September 2015 prepared as areal rainfall and then plotted according to the categories above normal, near normal and below normal. Probabilistic rainfall forecasts were prepared using above mentioned two models. The results of the each model compared with the observed rainfall map.

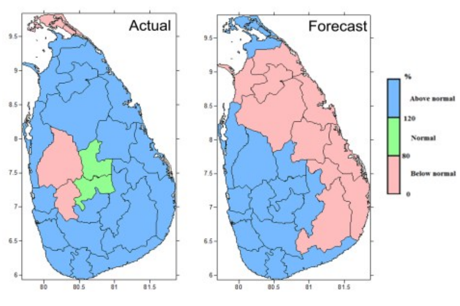

Fig 9: Actual and Forecasted probabilistic rainfall maps for month of September 2015

The results of the model which developed using CFS hindcast SST data indicate a virtuous accuracy forecast for southwest part of the country when comparing with the observations (Fig 9). Further any strong large scale forcing was unable to capture by zonal wind at 850hpa. Therefore, the model outcomes show poor skill in forecasting the rainfall for month of September.

Conclusion

The prediction of rainfall by statistical or empirical methods is feasible if there is a lagged relationship between the rainfall and suitable predictors. Seasonal predictability is strongly influenced by the slowly varying boundary forcing like sea surface temperatures. However, the predictability is limited to some extent due to the strong day-to-day atmospheric variability caused by the passage of the synoptic scale systems.

The first step towards developing a reliable seasonal rainfall forecast is identifying the key predictors that drive rainfall. This paper investigates the lag relationships between rainfall across Sri Lanka versus 3 atmospheric-oceanic predictors which are SST, zonal wind and meridional winds with one-month lead time for September rainfall which has significant economic importance since the main agriculture season “Maha” starts in September.

Composite analysis technique was carried for the large-scale atmospheric variables for anomalous positive rainfall years as well as anomalous negative rainfall years to identify the best predictors as well as the best domains which have significant impact on the September monthly rainfall over Sri Lanka. Canonical Correlation Analysis model was developed to predict September rainfall using SST, Zonal and Meridinal wind at 850mb and 500mb as the predictors. The CCA defines spatial pattern relationships between global SST and September district rainfall over Sri Lanka.

SST over central equatorial Pacific in August is the best predictor for September rainfall over Sri Lanka according to the forecast verification. Prediction was able to capture the observed rainfall for the Southwestern parts very well.

Prediction skill is poor in other two variables such as Zonal and Meridinal wind at 850mb and 500mb. In general since the month of September is sandwiched between the tail end of southwest monsoon and beginning of second inter-monsoon, the rainfall prediction one month ahead is difficult. The scale interaction between large-scale southwest monsoon circulation and convective activity associated with formation of mesoscale circulation due to differential heating may play an important role during this month.

The relationships between predictor and predictant have to be tested periodically and new predictors need to be identified for the improvements of these models.

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