EXPERIMENTAL PROBABILISTIC RAINFALL FORECAST FOR DIFFERENT DISTRICTS IN SRI LANKA USING CLIMATE PREDICTABILITY TOOL

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ABSTRACT

Statistical models were developed to forecast the probability of receiving monthly total rainfall for 25 districts of Sri Lanka using the canonical correlation analysis (CCA). Seasonal forecasts are generally provided by General Circulation Model (GCM) products such as the Climate Forecasting System (CFS) model developed by National Centers for Environmental Prediction (NCEP). These seasonal forecasts 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.

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 previous months. 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 best predictors as well as best domains which have significant impact on the monthly rainfall over Sri Lanka. The levels and sources of predictive skills have been explored for different predictors such using a Relative Operational Characteristic (ROC) diagram.

Results indicate that zonal wind at 500 mb level over the Indian Ocean (20°N-25°S latitude and 40°E–120°E longitude) has the highest overall predictability for January forecast. ROC diagram shows good skill for predicting above normal rainfall (0.75) and below normal rainfall (0.83) for January forecasts. For February forecast, SST over Tropical Equatorial Pacific has the highest overall predictability with good skill for predicting above normal rainfall (0.8) and below normal rainfall (0.7).

However, for April forecast, zonal wind at 850 mb level over the Indian Ocean and the Pacific Ocean has the highest overall predictability but shows poor skill for predicting above normal rainfall (0.49) and below normal rainfall (0.5). It is recognized that the model shows poor skill for April forecast partly due to likely absence of any strong large scale forcing during the inter-monsoon season.

INTRODUCTION

The climate of Sri Lanka is essentially monsoonal, dominated by the South-West and North-East monsoons, on which the life and economy of the island is critically dependant. On the other hand the country exhibits typical characteristics of tropical weather owing to its latitudinal position. The two monsoons together account for about 2/3 of the year, clearly demonstrating the importance of the monsoons to the region and the rainfall associated with them. The significant anomalies in climate are mainly decided by the temporal and spatial variations of rainfall, which have a strong impact on the weather-sensitive socioeconomic activities such as agriculture, water resource management and hydro power generation.

The production of rice, which is one of principal crops of Sri Lanka, is highly susceptible to rainfall variability; both deficient and excess rainfall conditions were found to have significantly contributed to reduction of rice yields.

To minimize the damages and associated risks of climate-related disasters, relevant authorities must practice effective climate risk management. Skillful seasonal climate forecasts are relevant to this issue.

Seasonal forecasts are generally provided by a general circulation model (GCM). GCM products such as the Climate forecasting system (CFS) seasonal forecasts could be useful for large scale regions such as the greater South Asian region; however, because of their coarse resolution of several hundred kilometers, they may have limited practicality for small-scale local administrative areas within the region. In addition to this, because of the difficulty of simulating rainfall processes, the rainfall forecast of GCMs may not be as skillful as other variables. However, GCMs can provide skillful seasonal forecasts of mean circulation, particularly in the tropics (e.g., Stockdale *et al.,* 1998; Charney and Shukla 1981), 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 (Feddersen and Andersen 2005; Chu *et al.,* 2008; Landman and Tennant 2000; Pavan *et al.,* 2005).

Statistical downscaling aims to specify the empirical relationships between the local-scale rainfalls (referred to as the predictand) and the large-scale field (referred to as the predictor). However, if the predictors used are dynamically predicted fields, the scheme is usually referred to as model output statistics (MOS). These relationships are then used to infer local changes by means of projecting the large-scale information onto the variability at local scale (Zorita and von Storch, 1999). The technique bridges the scale differences between the coarse resolutions of the GCM output and the local-scale precipitation, and it also possibly corrects the GCM's systematic errors. The major drawback of this approach is the need for a long series of hindcast data of an unaltered model. Every time the GCMs undergo a major update, a long series of hindcast must be recomputed to derive a new empirical relationship between the predictands and predictors.

METHODOLOGY

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 target rainfall (or the predictand) data were provided by the Department of Meteorology (DOM) Sri Lanka. Areal district rainfall estimated using Kriging interpolation with spline interpolation (Watson, 1984) at 0.025° x 0.025° resolution using entire DOM rainfall database. Both the predictor field and the precipitation field span a common period of 31 years from 1982 to 2012.

NCEP reanalysis data (Kalnay *et al.,* 1996) over the region between 20°E to 80°W and 40°S to 40°N was used for composite analysis to study the large scale anomalous weather features which can impact the monthly district rainfall.

Climate Predictability Tool (CPT)

The CPT is a software package developed by the International Research Institute for Climate and Society (IRI) designed for making seasonal climate forecasts. There are two main approaches for generating seasonal forecasts: using large-scale models of the global atmosphere, known as general circulation models (GCMs), or using a statistical approach to relate seasonal climate to changes in sea-surface temperatures, or to other predictors. Because of the coarse scale at which the GCMs operate, the geography in the models is often distorted, and so geographical locations can be displaced. These GCM outputs therefore need to be adjusted so that they can be applied at the local level. The CPT tool is designed to perform both forms of prediction, namely downscaling of GCM output, and purely statistical predictions (www.nws.noaa.gov/ost/climate/STIP/36CDPW/36cdpw-smason.pdf.). In this study statistical downscaling of Climate Forecasting System (CFS) predictions was carried out using Canonical correlation analysis (CCA).

Canonical Correlation Analysis (CCA)

Canonical correlation analysis, which is often used as a forecast technique (Barnston and Ropelewski, 1992; Barnston, 1994), is a multivariate statistical methodology to determine linear combinations of two data sets (the predictor data set, e.g. sea-surface temperature, and the predictand data set, e.g. rainfall) that are highly correlated. In this study, this technique was used in downscaling the CFS output variables as a predictor. In both cases the predictor and target fields were pre filtered separately using the empirical orthogonal function analysis (EOF; e.g., Jackson 1991). For the downscaling experiment, the CCA was applied by linking each of predictor variables to the local precipitation field.

Composite analysis technique

Composite analysis technique was carried for zonal wind at 850, 500, and 250-hPa 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 significant impact on the monthly rainfall over Sri Lanka. Climatological mean of NCEP/NCAR reanalysis data from 1971 to 2000 are used to analyze the anomalies.

RESULTS AND DISCUSSION

The best predictor large-scale field

For January, above normal rainfall was received in years 1984, 1986, 1990, 1991, 1995, 2000 and 2006 and below normal rainfall received in years 1980, 1982, 1983, 1988, 1993, 1997, 2009 and 2010. The composite image of the zonal wind anomaly at 500 mb level during above normal rainfall years (right) and below normal rainfall years (left) indicates positive anomalies over west Indian Ocean between 10°N to 20°N and 45°E to 60°E and over South China sea between 10°N to 20°N and 95°E to 135°E during negative rainfall years while negative wind anomalies over the same region during positive rainfall years. (Fig.1) Further negative wind anomalies to the south of Sri Lanka can be seen during negative rainfall years and positive wind anomalies evident in positive rainfall years but the position has moved southward. Zonal wind at 500 mb level over the Indian Ocean and West Pacific Ocean can be used as the best predictor for January.

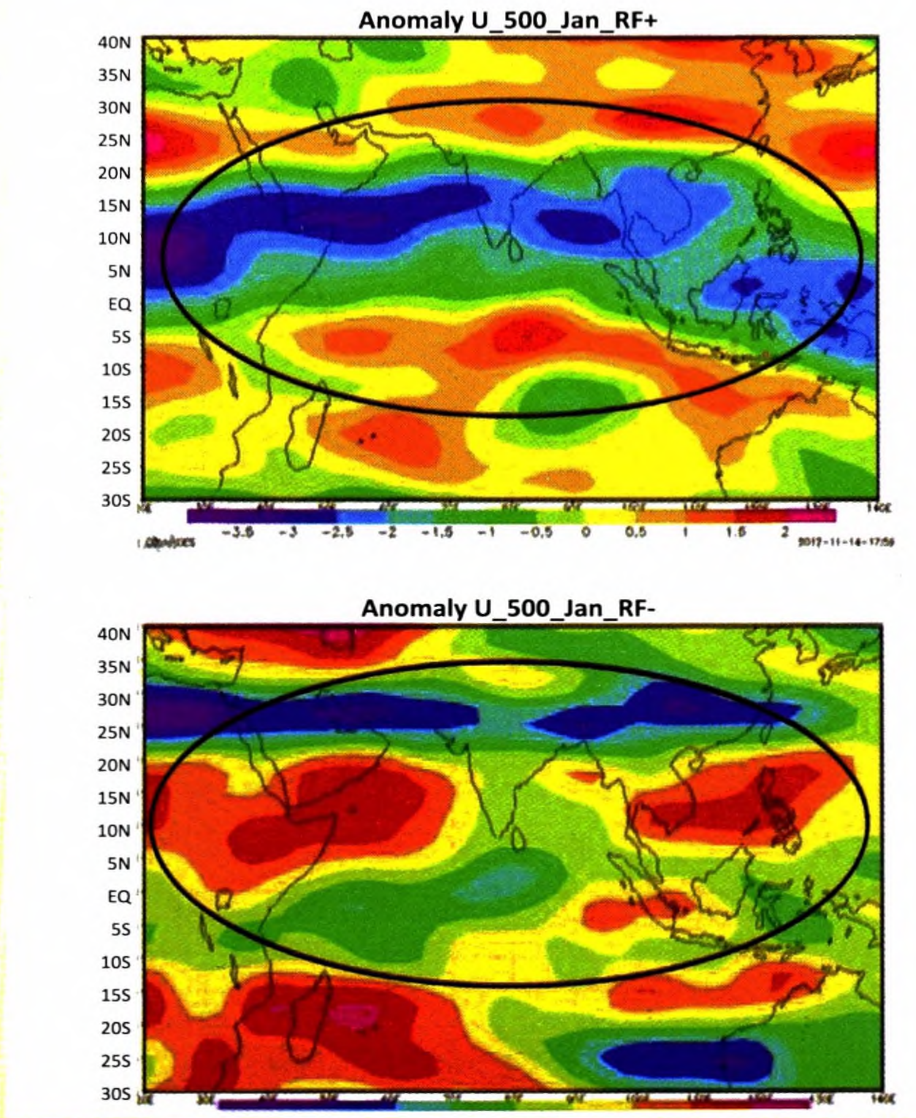

Fig. 1. Zonal wind anomaly at 500 mb level during above normal rainfall years (above) and below normal rainfall years (below) for January

Above normal rainfall was received for February in 1984, 1985, 1994, 1996, 1999, 2000 and 2008 while below normal rainfall was received in 1980, 1982, 1983, 1989, 1997, 2007 and 2009. Fig. 2 is the composite image of the Sea Surface Temperature(SST) anomaly during above normal rainfall years (above) and below normal rainfall years (below). Negative SST anomalies can be seen over the Central Equatorial pacific and over the cold tongue located along West South American coast during positive rainfall years. These negative SST anomalies over the Central Equatorial pacific and over the cold tongue are typical features associated with *LaNina* conditions. During negative rainfall years positive SST anomalies are evident over the cold tongue which is a typical *ElNino* feature but slightly negative SST anomalies still present over the Central Equatorial pacific. SST over the equatorial Pacific Ocean can be used as the best predictor for February.

For April, below normal rainfall was received in 1983, 1985, 1991, 1994, 1997, 1998, 2000, and 2006 and above normal rainfall received in 1984, 1995, 1999, 2001, 2002, 2008, and 2011. Figures 3, 4, and 5 are the composite images of Zonal wind anomaly at 850 mb level, Zonal wind anomaly at 500 mb level and the Sea Surface Temperature (SST) anomaly, during above normal rainfall years (above) and below normal rainfall years (below) respectively. However for April a robust signal associated with negative and positive rainfall over Sri Lanka cannot be found out from the composite analysis of these three variables.

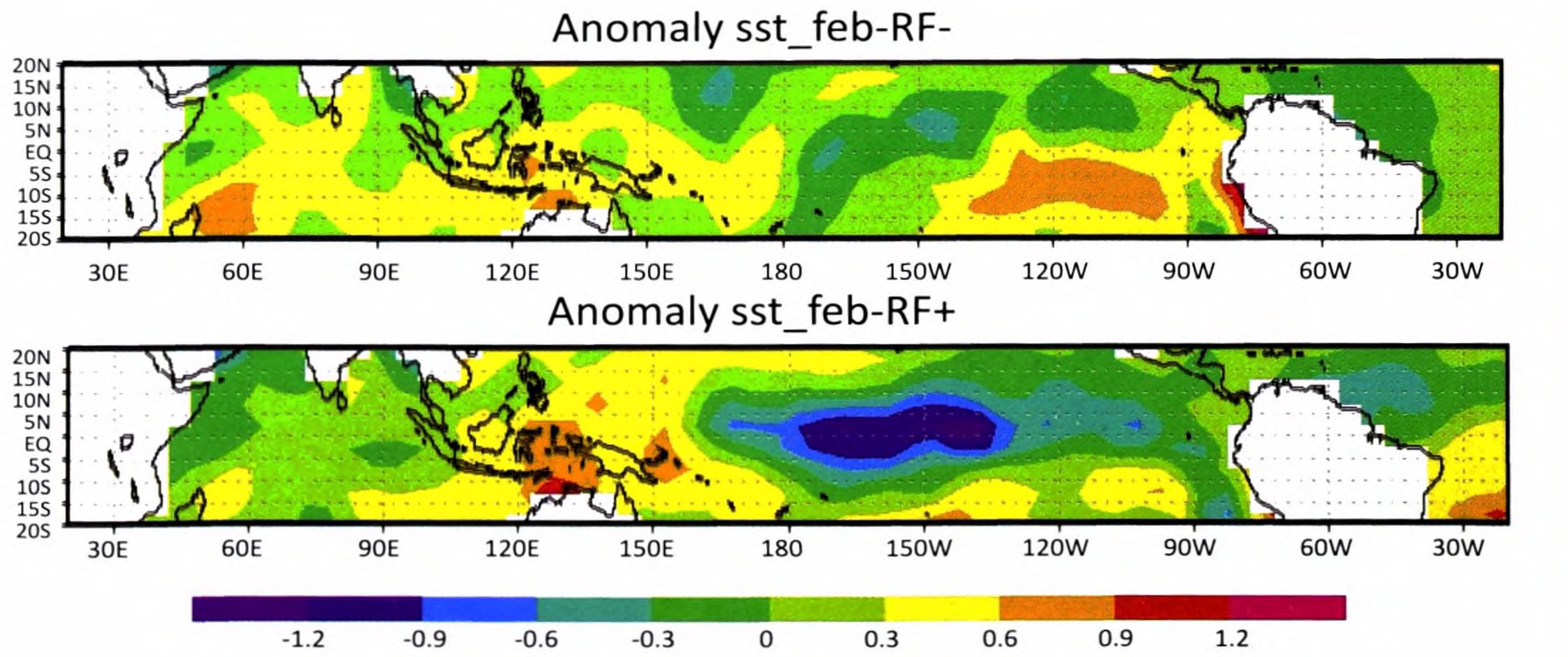

Fig. 2. Composite image of the sea surface temperature (SST) anomaly during negative normal rainfall years (above) and positive normal rainfall years (below) for February

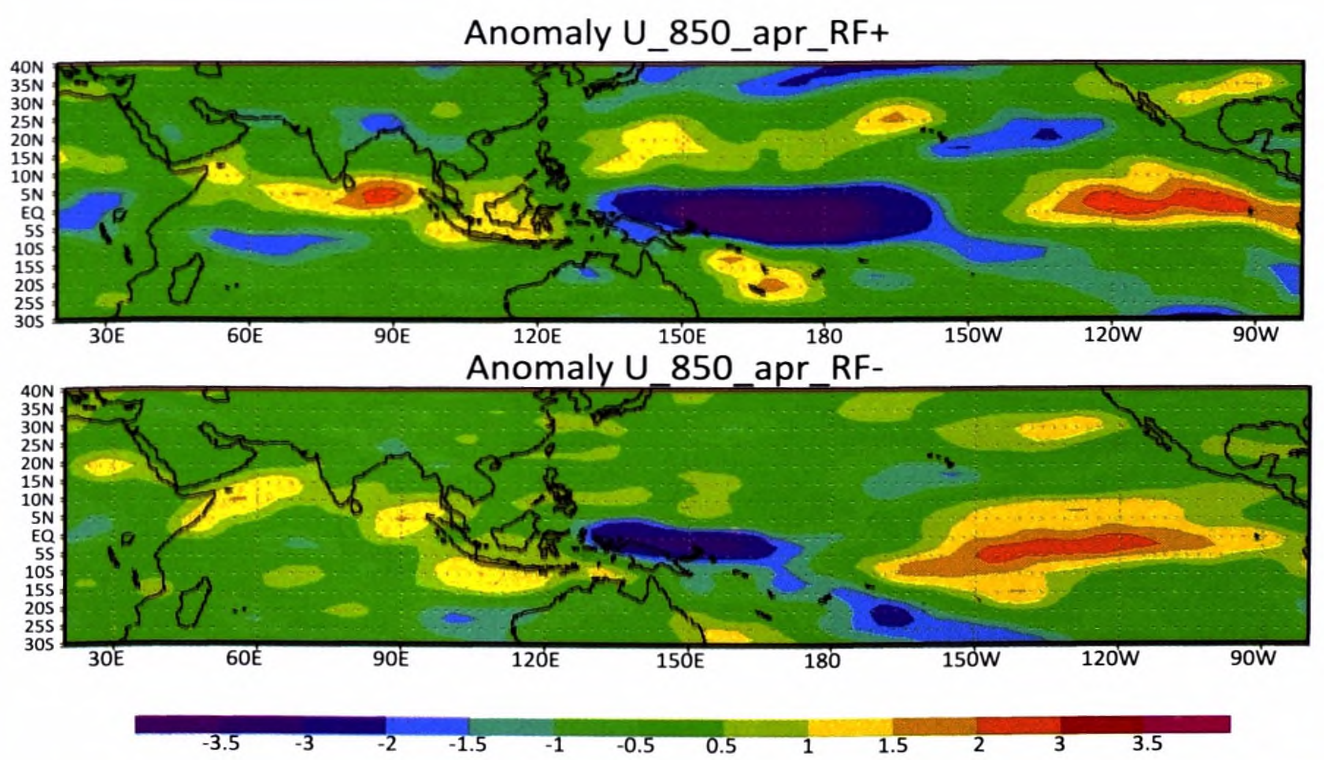

Fig. 3. Zonal wind anomaly at 850 mb level during above normal rainfall years (above) and below normal rainfall years (below) for April

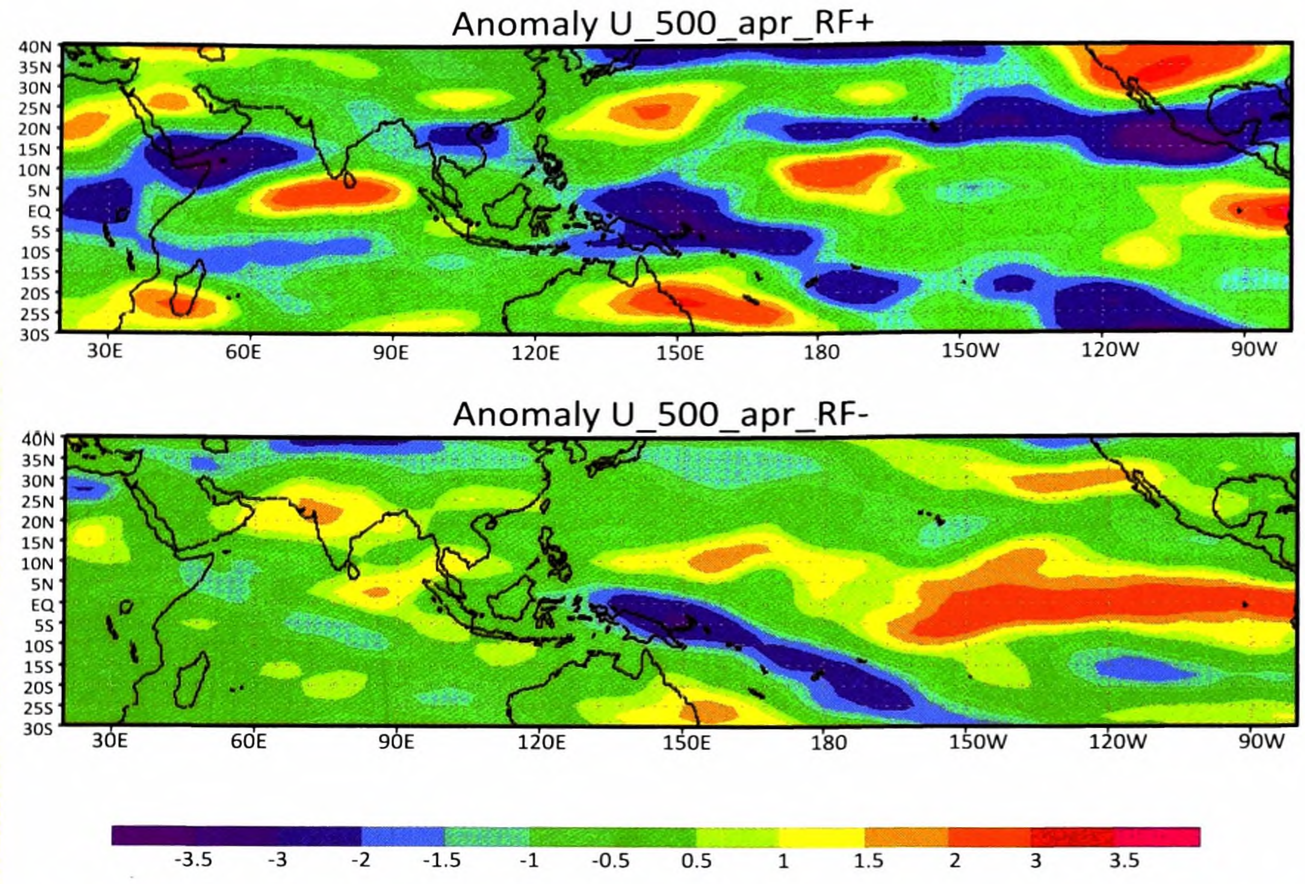

Fig. 4. Zonal wind anomaly at 500 mb level during above normal rainfall years (above) and below normal rainfall years (below) for April

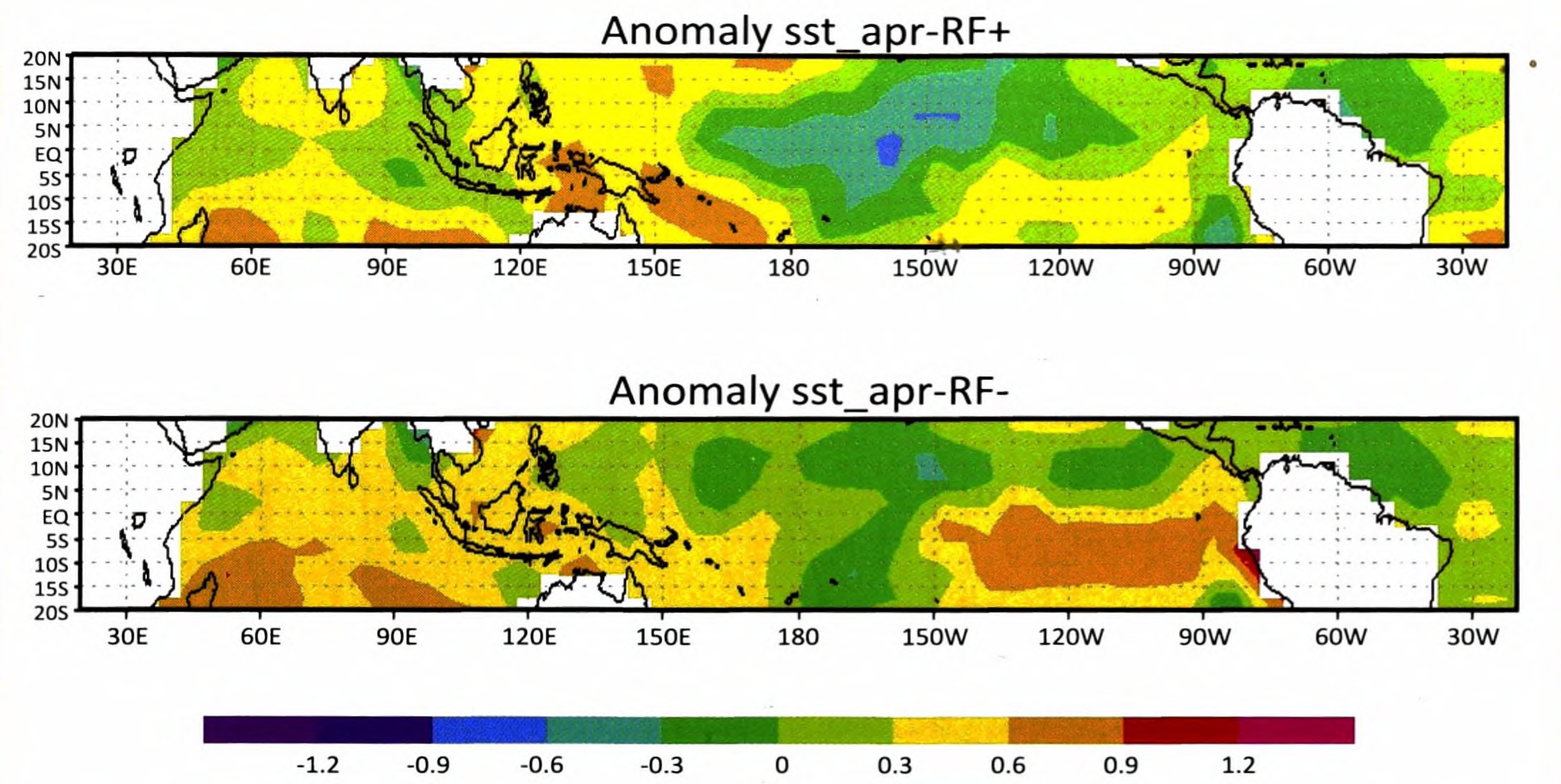

Fig. 5. Composite image of the sea surface temperature (SST) anomalies during positive rainfall years (above) and negative rainfall years (below) for April.

Statistical monthly rainfall forecast models

To predict monthly rainfall, regression models are built using cross validated CCA between CFS hindcast data of 500 mb zonal wind over the tropical Western Pacific and Indian Oceans (20°N-25°S latitude and 40°E–120°E longitude), CFS hindcast data SST over the tropical Pacific Ocean (20°N-25°S latitude and 100°E–80°W longitude), and CFS hindcast data of 850 mb zonal wind over the tropical Pacific and Indian Oceans (30°N-30°S latitude and 30°E–90°W longitude as predictors and Areal district rainfall as predictands for January, February and April respectively. The models were built using the Climate Predictability Tool (CPT) software developed at the International Research Institute for Climate Prediction (IRI; http://iri.columbia.edu/outreach/software/). Hindcast CFS data spanning a period of 30 years from 1982 to 2012 with initial conditions from the

1st week of the previous months were used in the models.

The predictor and 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. Homogeneous correlation maps of the leading CCA mode are shown in Figs. 6, 7 and 8 for 500 mb Zonal wind, SST and 500mb Zonal wind, respectively. The first CCA mode exhibit features present during *El Nino* events (Fig. 7) associated with below normal rainfall in February.

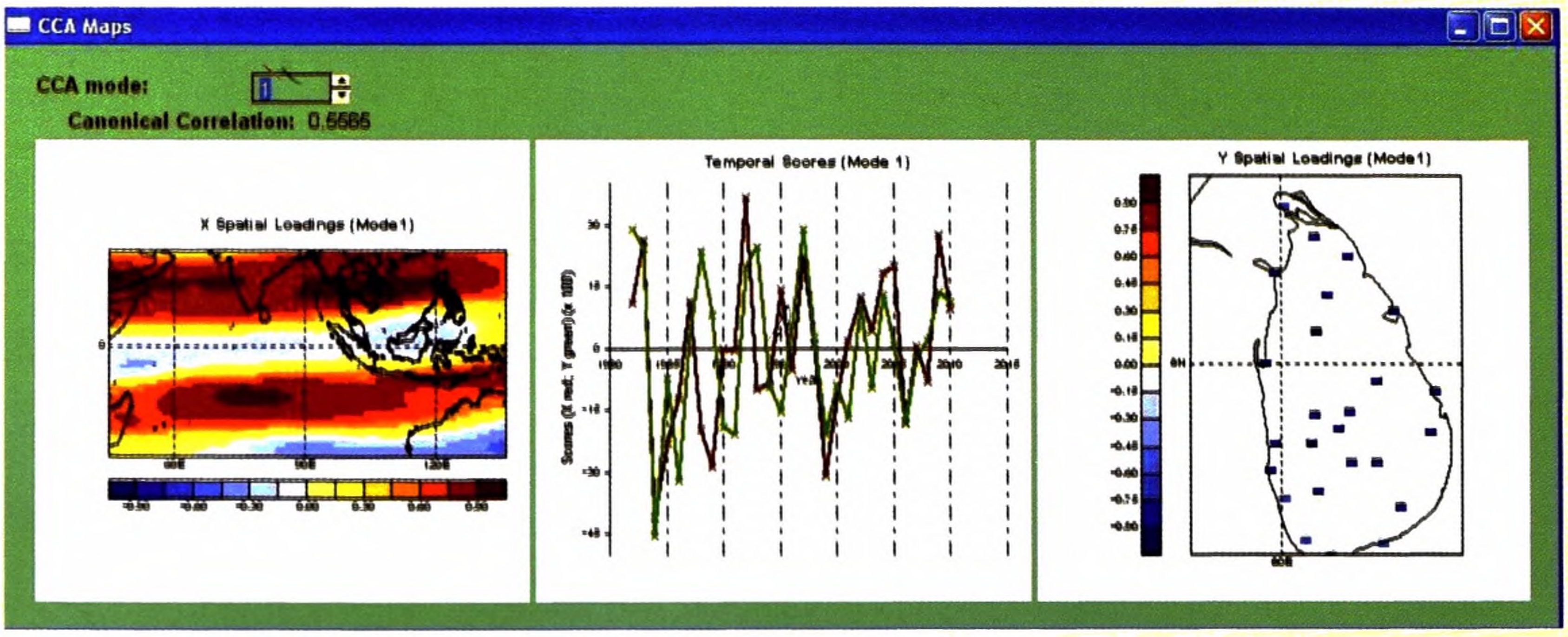

Fig. 6. Mode of CCA, with zonal wind at 500 mb as predictor and monthly rainfall for January as predictand.

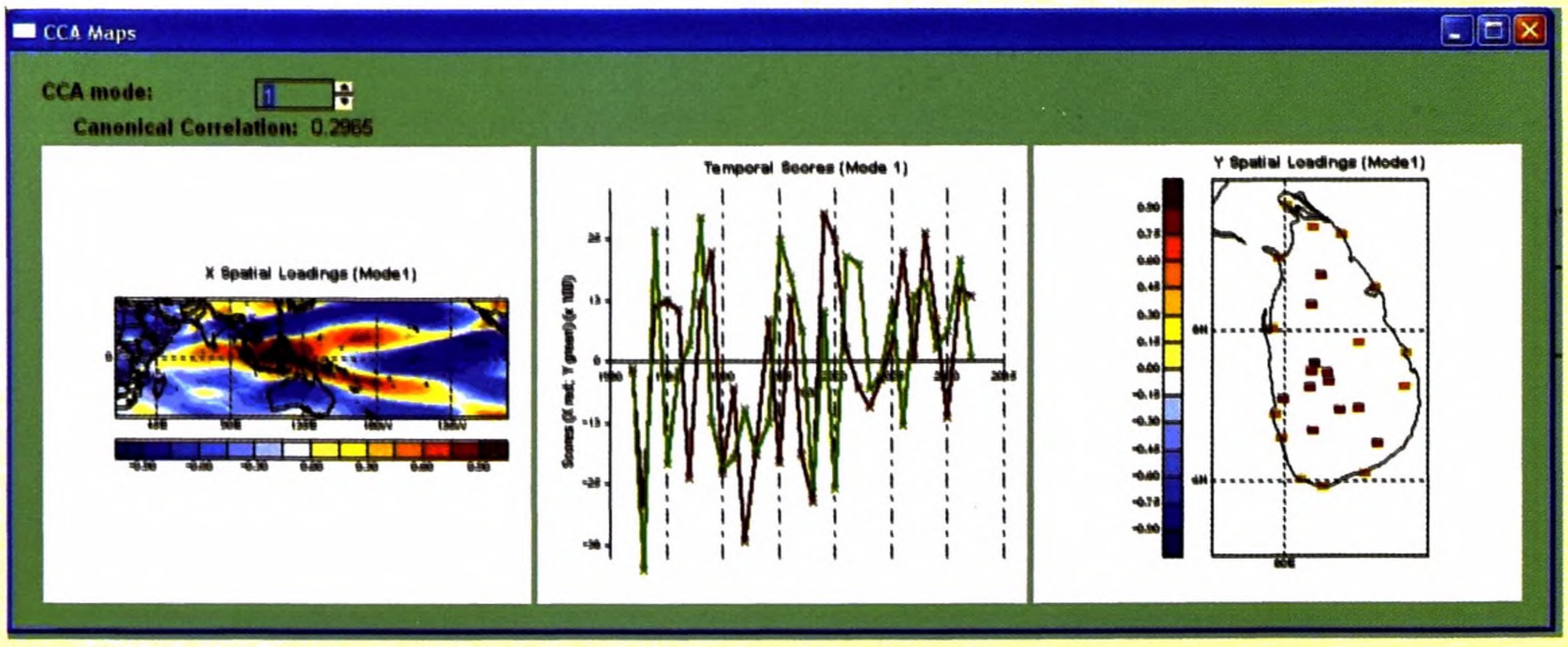

Fig. 7. Mode of CCA, with SST as predictor and monthly rainfall for February as predictand.

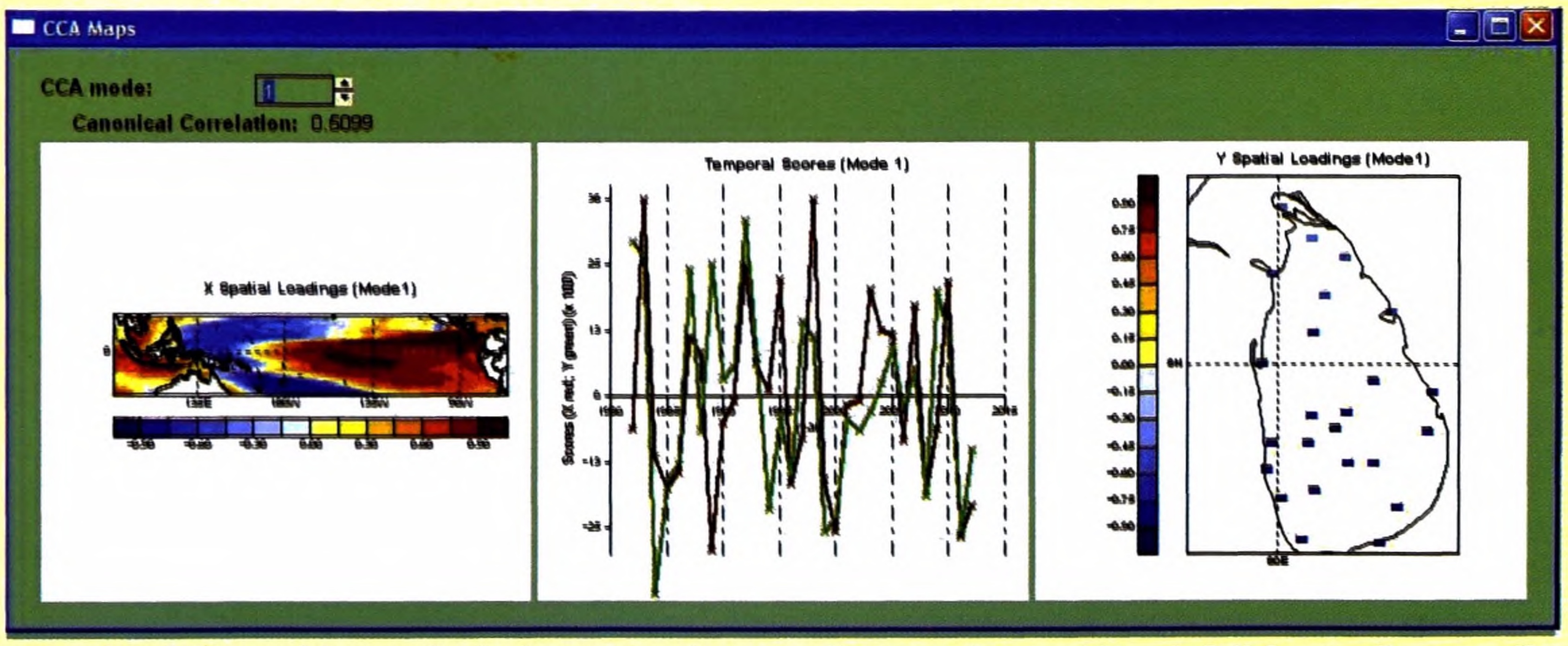

Fig. 8. Mode of CCA, with zonal wind at 850 mb as predictor and monthly rainfall for April as predictand.

Forecast verification

The relative operating characteristic (ROC) is a representation of the skill of a forecast system in which the hit rate and the false-alarm rate are compared. Both ratios can be calculated simply from the contingency table (Mason, 1982). ROC diagram for the statistical model developed to forecast January rainfall probabilities (Fig. 9) shows good skill for predicting above normal rainfall (0.75) and below normal rainfall (0.83). The ROC diagram for the statistical model developed to forecast February rainfall probabilities also indicates good skill for predicting above normal rainfall (0.8) and below normal rainfall (0.7). (Fig. 10)

However, for the model developed to forecast April rainfall shows poor skill for predicting above normal rainfall (0.49) and below normal rainfall (0.5) (Fig. 11). It is recognized that the model shows poor skill for April forecast partly due to likely absence of any strong large scale forcing during the inter-monsoon season.

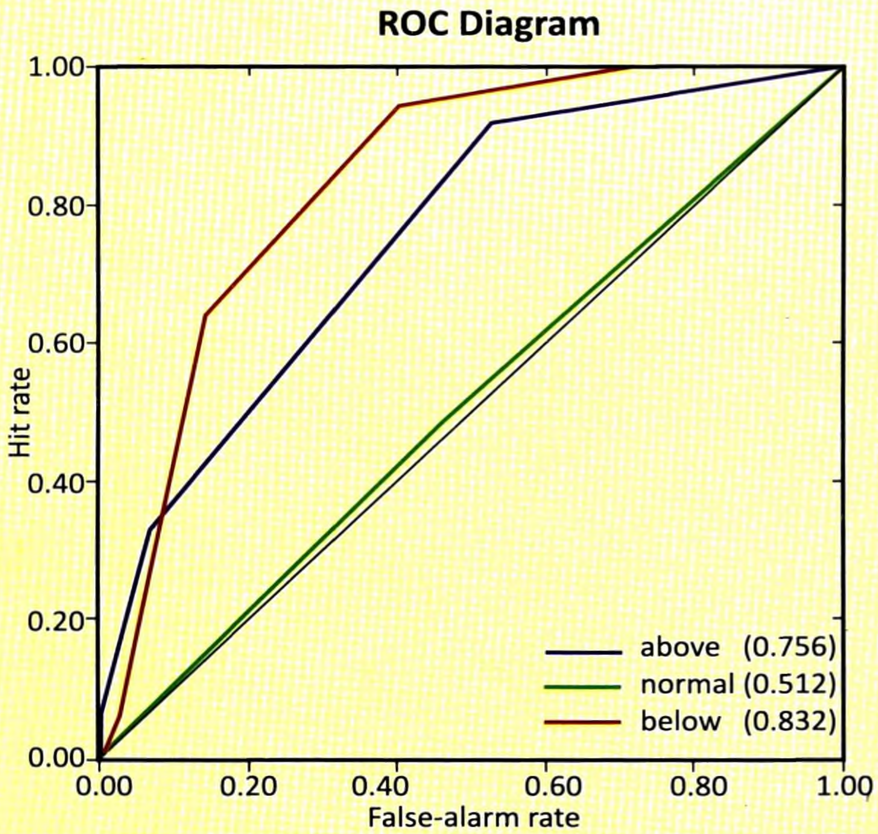

Fig. 9. Relative operational characteristic (ROC) diagram for January forecast

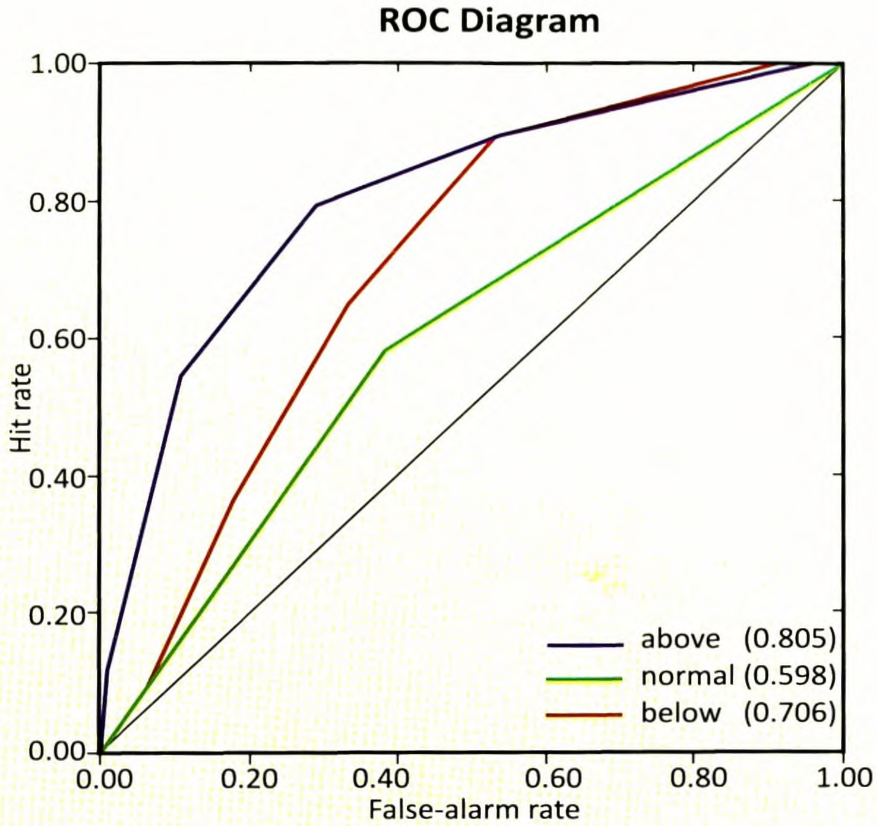

Fig. 10. Relative operational characteristic (ROC) diagram for February forecast

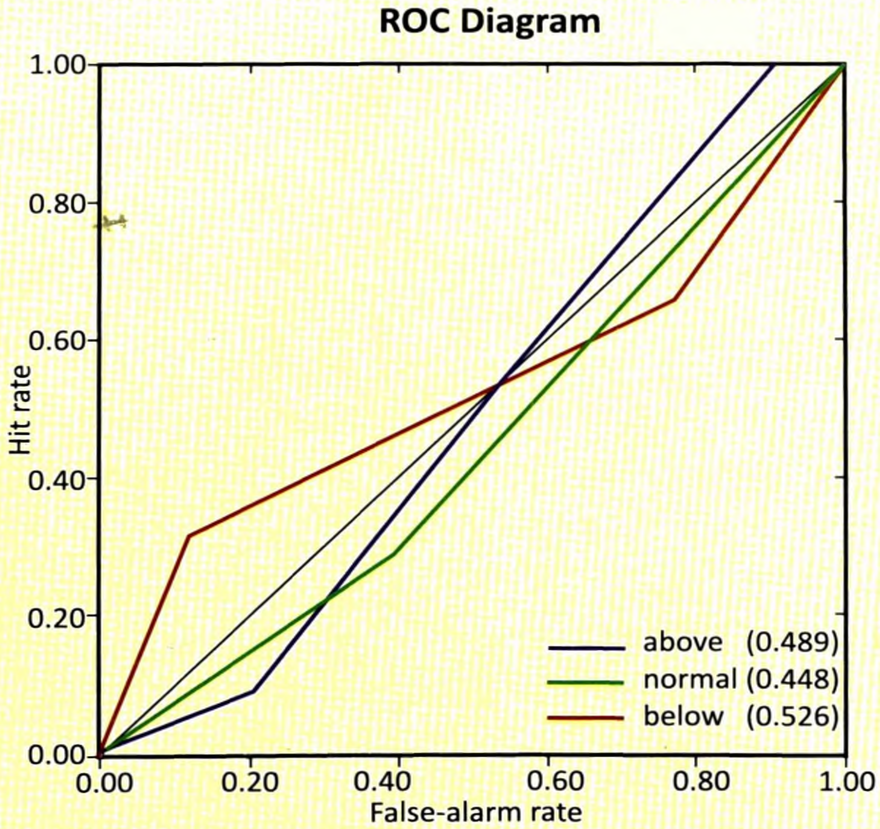

Fig. 11. Relative operational characteristic (ROC) diagram for April forecast

CONCLUSIONS

CCA based statistical models were developed for forecasting monthly rainfall for 25 districts of Sri Lanka in experimental basis. Statistical downscaling of CFS predictions was carried out. For downscaling, zonal 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 previous months. 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 best predictors as well as best domains which have significant impact on the monthly rainfall over Sri Lanka. The levels and sources of predictive skills have been explored for different predictors such using a Relative Operational Characteristic (ROC) diagram. Statistical models developed to forecast January and February rainfall shows good skill for predicting above normal rainfall as well as below normal rainfall but the model developed to forecast April rainfall, shows poor skill for predicting both above normal rainfall as well as below normal rainfall. It is recognized that the model shows poor skill for April forecast partly due to likely absence of any strong large scale forcing during the inter-monsoon season.

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