Modeling the Influence of Large-Scale Circulation Patterns on Precipitation in Mauritius

Kreshna Gopal
Scinova Consulting Ltd.
Mauritius
kgopal@scinova.com

C Prakash Khedun
Scinova Consulting Ltd.
Mauritius
pkhedun@scinova.com

Anoop Sohun
Scinova Consulting Ltd.
Mauritius
asohun@scinova.com

***Abstract*—Mauritius suffers from chronic water shortages that can severely impact its economy and the well-being of its population. Both surface and groundwater availability are determined by rainfall, which is in turn influenced by large-scale circulation patterns such as the El Niño Southern Oscillation (ENSO) and the Indian Ocean Dipole (IOD). Here we report on the influence of these two teleconnection patterns and present the result of a simple neural network for precipitation forecasting, based on the state of ENSO and IOD. Data from the Vacaos station, for the period 1961 to 2012 is used. We found statistically significant correlation between average winter rainfall and ENSO and IOD indices. The correlation for summer was negligible. The prediction of summer precipitation was less accurate than that of winter precipitation. The findings from this study can help in more efficient planning and management of water resources on the island.**

Keywords—precipitation, ENSO, IOD, neural network.

I. Introduction

The water shortages that Mauritius regularly faces is alarming. Based on the United Nations' definition [1], Mauritius is a water stressed country. The Water Resources Unit in Mauritius predicts that by 2020, the country will slip into the water scarce category [2]. Furthermore, the island does not have enough carry-over capacity, i.e. most of the water received during a hydrologic year is used within the year itself. Thus, a shortage of rainfall can have immediate and disastrous effects on the well-being of the population.

We conducted a comprehensive study [3] where we (i) investigated the relationship between the El Niño Southern Oscillation (ENSO) and the Indian Ocean Dipole (IOD) with precipitation, (ii) developed a precipitation forecasting model using artificial neural network, and (iii) conducted a bivariate drought analysis using multiple precipitation deficit variables (duration, severity, and inter-arrival time).

In this paper, we present one component of this study, which is establish the relationship between large-scale circulation patterns (ENSO and IOD) on precipitation in Mauritius and use these indices to predict precipitation using a neural network. A predictive model can enable medium- and long-term planning and facilitate proactive measures for forecasted water shortages and droughts.

II. Data

A. Precipitation Data

Monthly precipitation data for the Vacoas station was obtained from two sources. Data for the period from 1961 to 1990 was obtained from the National Climate Data Center (NCDC) which is part of the Global Historical Climatology Network (GHCN). Data beyond 1990 was not available from the NCDC and was purchased from the Mauritius Meteorological Services (MMS). Fig. 1 gives a plot of the monthly precipitation for January 1961 to September 2012, along with the long-term mean (170.54 mm). It is apparent that the precipitation is not uniform or close to the long-term mean but is highly variable. For most months, the precipitation is below the long-term mean, and for some months, the precipitation is several magnitudes above the long-term mean.

The largest variation in precipitation is noted for February followed by January, which are also the two wettest months. One notable outlier is in December, where in December 1961, the monthly total was 1,362 mm. The median for precipitation is generally lower than the long-term mean for each month, which implies a slight positive skewness in monthly precipitation.

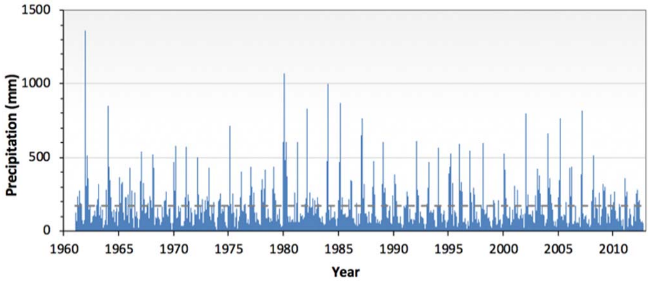

Fig. 1. Monthly precipitation at Vacoas (1961 – 1990). The dotted gray line represents the long-term mean (170.54 mm) for the dataset.

B. El Niño Southern Oscillation

Several indices are available for ENSO, including the Southern Oscillation Index (SOI), Niño 3, Niño 4, Niño 3.4, the Multi ENSO Index (MEI), among others. The Niño 3.4 index [4] has been employed in a number of hydro-meteorological studies because it often exhibits the strongest influence and correlation on remote hydro-climatological events. It is the area-averaged sea surface temperature anomaly (SSTA) over the region bounded by 5°N–5°S and 120°W–170°W.

Trenberth [5] also proposed the use of the Niño 3.4 index for the definition of El Niños, and an "El Niño can be said to occur if 5-month running means of sea surface temperature (SST) anomalies in the Niño 3.4 region exceed 0.4°C for 6 months or more." The opposite can be adopted for the definition of La Niña events. Other definitions, with slight variations of the one proposed in [5], have since been proposed and adopted in different regions of the world. No official definition for El Niño or La Niña has been developed or adopted for Mauritius.

Monthly data for the Niño 3.4 index was obtained from the International Research Institute on Climate and Society Data Library. Fig 2 shows a plot of the Niño 3.4 index for the period January 1961 to July 2009. Sustained positive (negative) anomalies are indicative of El Niño (La Niña) conditions. The Niño 3.4 index is overlain with a 5-month moving average and the ±0.4 thresholds.

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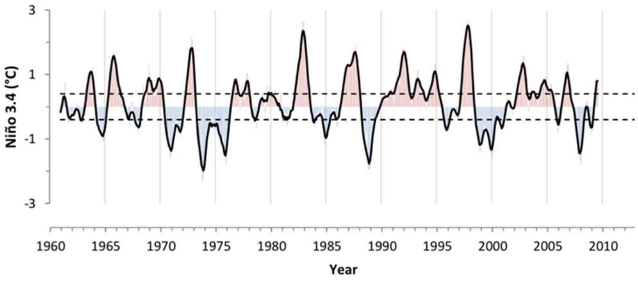

Fig. 2. Time series of Niño 3.4 index smoothed with a 5-month moving average and ±0.4 thresholds (broken lines).

C. Southern Oscillation Index

The Southern Oscillation Index (SOI) is an index that shows the variation in the Southern Oscillation. It is the difference in mean sea level pressure anomalies at Tahiti and Darwin, Australia. Data for the SOI was obtained from the National Center for Atmospheric Research (NCAR) Climate and Global Dynamics (CGD).

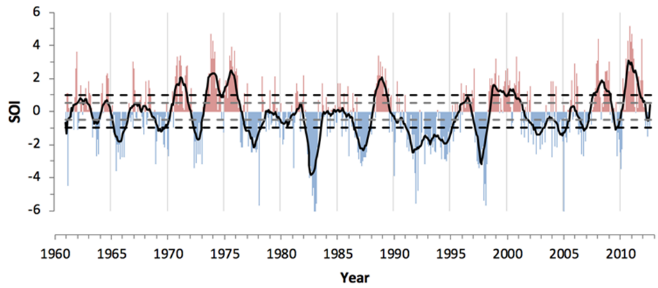

Fig. 3. Time series of the Southern Oscillation Index (SOI) overlain with a 13-month moving average and ± 0.5 and ± 1 thresholds.

Fig. 3 shows a plot of SOI for the period 1961 to 2012. The data is smoothed with a 13-month centered moving average to highlight the positive and negative phases. Note that the SOI is negatively correlated with the Niño 3.4 index, i.e. an El Niño (La Niña) will be represented by positive (negative) Niño 3.4 indices and the SOI will be negative (positive). The strength of El Niño and La Niña events can be gauged based on the scale given in Table I.

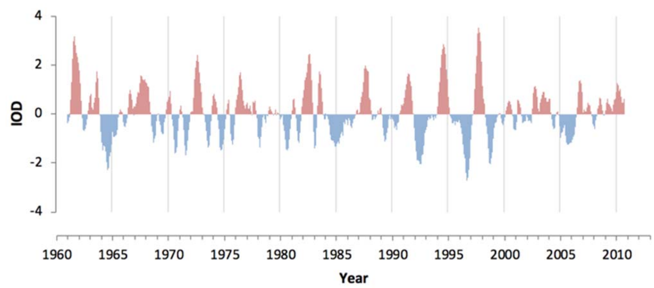

Fig. 4. Time series for IOD.

D. Indian Ocean Dipole

IOD is defined as the anomalous SST gradient, known as the Dipole Mode Index (DMI), between the western equatorial Indian Ocean (50°E-70°E and 10°S-10°N) and the south eastern equatorial Indian Ocean (90°E-110°E and 10°S-0°N). DMI data was obtained from the Japan Agency for Marine-Earth Science and Technology (JAMSTEC). Fig. 4 is a plot of the DMI for the period January 1961 to September 2010. Data beyond the latter date was not available.

III. Relationship Between Large-Scale Circulation Patterns and Precipitation

The correlation between the climate indices and precipitation was determined using Pearson correlation. The correlation coefficient, ρ_{xy}, is a measure of linear association between two time series x and y and is given by

$$\rho_{xy}(k) = \frac{E\left[(x_i - \mu_x)(y_{i+k} - \mu_y)\right]}{\sigma_x \sigma_y} \qquad (1)$$

where $\rho_{xy}(k)$ is the cross-correlation for lag k between time series x_i and y_i with means μ_x and μ_y and standard deviation σ_x and σ_y respectively, and $E[\cdot]$ is the expectation operator. The range for $\rho_{xy}(k)$ is [-1, 1], with larger $|\rho_{xy}|$ implying stronger association between x and y.

Mauritius has two seasons: winter and summer. Winter lasts from May to October and summer is from November to April. November is also the beginning of the hydrological year. In order to assess the influence of ENSO and IOD on precipitation at Vacoas, the precipitation series was divided into two series, winter and summer, and the average precipitation for each year was computed. The Niño 3.4, SOI and IOD series were similarly divided into two sets.

The correlation between Niño 3.4, SOI, and IOD with average winter and summer precipitation were computed. The magnitude and sign of the correlation coefficient indicates the existence, strength, and nature of any influence the teleconnection phenomena have on precipitation.

A. Correlation between Precipitation and SOI

Table I gives the correlation coefficient and p-values for the correlation between precipitation anomaly and the two ENSO indices, which is the difference between the average precipitation for each year and the long term mean for the season. We divided the data into two periods (1961-1990 and 1991-2009) because they come from different sources. We also do the analysis for the combined periods (1961-2009). No trend is apparent in the summer plot, but a small negative trend, above average rainfall with negative SOI, is visible in the winter plot.

Note that the correlation between Niño 3.4 and precipitation is of opposite sign compared to SOI and precipitation, because Niño 3.4 and SOI are negatively correlated.

There exists a small correlation between winter indices and precipitation, for the 1961-1990 series, while there is no apparent correlation between the indices and summer precipitation. The correlation is not statistically significant at an alpha of 0.05 but statistically significant at an alpha of 0.1. The correlation between SOI and winter precipitation is stronger than that between Niño 3.4 and precipitation. Even though both phenomena are related, stronger correlation with SOI has often been observed. One possible explanation can be that SOI is an Indo-Pacific phenomenon and recorded closer to Mauritius while Niño 3.4 is recorded further away from Mauritius. Furthermore, precipitation may respond better or faster to atmospheric fluctuations than to changes in SST. Thus SOI may be a better index for the purpose of this study. The fact that there is a correlation between winter SOI and precipitation anomaly in the 1961-1990 series but no correlation with the 1991-2012 or 1961-2012 series suggest that the series may be inhomogeneous.

TABLE I. CORRELATION COEFFICIENT BETWEEN ENSO INDICES AND PRECIPITATION ANOMALY AT VACOAS. NUMBERS IN BRACKET ARE THE P-VALUES

Index	Period	Winter	Summer
Niño 3.4	1961-1990	0.237 (0.208)	0.031 (0.875)
	1991-2009	0.065 (0.797)	0.296 (0.219)
	1961-2009	0.161 (0.276)	0.075 (0.610)
SOI	1961-1990	−0.329 (0.076)	−0.015 (0.941)
	1991-2012	0.042 (0.858)	−0.348 (0.113)
	1961-2012	−0.184 (0.198)	−0.118 (0.411)

B. *Correlation between Precipitation and IOD*

Table II gives the correlation between average IOD index and average precipitation anomaly for winter and summer. The correlation for three different periods was computed. A positive, statistically significant, correlation exists between average winter IOD and precipitation anomaly at Vacoas.

TABLE II. CORRELATION COEFFICIENT BETWEEN IOD INDEX AND PRECIPITATION ANOMALY AT VACOAS. NUMBERS IN BRACKET ARE THE P-VALUES

Index	Period	Winter	Summer
IOD	1961-1990	0.375 (0.041)	0.108 (0.572)
	1991-2009	0.210 (0.388)	0.135 (0.482)
	1961-2009	0.309 (0.031)	0.124 (0.394)

IV. PRECIPITATION PREDICTION USING NEURAL NETWORKS

C. *Methods*

An artificial neural network (ANN) is an approach inspired by the biological neural networks in the brain. Through a connectionist approach, it aims to process information, through a collection of nodes, called artificial neurons. ANNs are employed in modeling the relationships between sets of inputs and outputs, often related through complex non-linear systems. In essence, they are non-linear statistical modeling tools.

An ANN is an adaptive system that changes its structure (like weights between connections) based on information provided to the network during a learning phase. It can then be used for the prediction of outputs given new input data.

Artificial neural networks normally consist of three layers: the input layer, the hidden layer, and the output layer. The input layer simply accepts inputs from the external environment, while the output layer presents the results obtained to the external environment. Hidden layers are various levels of transformation of the data to establish the connection between inputs and outputs. The number of hidden layers varies; hidden layers may even be absent in certain types of neural networks.

An ANN has i number of inputs (x_i) and an output y. A weight (w_i) is associated with each input. Often, an additional parameter (w_0), called a bias, is included. The single neuron is a feed-forward device, that transforms a given input into some output. The activation, a, of the neuron is calculated according to the inputs x:

$$a = \sum_i w_i x_i \tag{2}$$

Then, the output y is set as a function $f(a)$. Back-propagation is the most widely used training algorithm [6]. It is a form of supervised learning, where the neural network is given a set of training examples. Each example consists of a pair of input and output and the input is typically represented by a series of values. The training set is used to iteratively update the weights of the interconnections so as to minimize an error function.

ANNs have been successfully used in a variety of applications such as medical diagnosis, vehicle control, recognition of faces and objects, e-mail spam filtering, game-playing, handwritten recognition, automated trading systems, etc. They have also been applied to a wide range of problems in hydrology, for example rainfall-runoff and streamflow forecasting [7, 8], flood and drought prediction [9, 10], etc.

An exhaustive review of the application of ANN in hydrology and water resources engineering is available in [11]

D. *Predicting Precipitation*

We have used an approach proposed in [12] that successfully used ANN for long range precipitation forecasting in California, USA. We started our tests trying to predict the yearly average precipitation, and then seasonal and monthly precipitation. We devised a series of tests to predict the seasonal average precipitation.

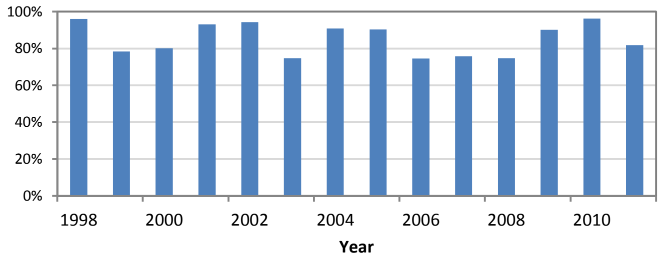

Fig. 5. Percentage accuracy of average winter precipitation using SOI.

For all the tests, 33 to 35 years of data have been used for training, 7 years of data has been used for validation, and 7 years of data have been used to test the neural network. Fig. 4 shows a representative result for the tests cases: the accuracy with which each year's average winter precipitation was predicted using SOI. The accuracies range from 74.8% to 96.2%, with an average of 86%. In general, we found that we could predict winter precipitation fairly accurately, while the prediction for summer are not as accurate. This corroborates with our statistical analysis.

V. DISCUSSION

The ability to accurately predict precipitation and drought conditions is a critical factor in the short, medium, and long-term water resources management. Precipitation is known to be influenced by large-scale circulation patterns. In

Mauritius, two major teleconnection patterns that are likely to affect rainfall are ENSO and IOD.

In this study, our focus was to assess the influence of these circulation patterns on precipitation on rainfall data recorded at Vacoas. The indices used are the Niño 3.4 index, the Southern Oscillation Index, and the Indian Ocean Dipole Mode Index for the period 1961 to 2012.

Our initial analysis revealed poor correlation between precipitation and these climate indices. However, when the data series were split into two separate seasons (winter and summer), higher correlations were obtained for winter. We then predicted precipitation using teleconnection indices as predictor variables. With neural networks, we obtained an average winter precipitation prediction accuracy of 86%. However, prediction of summer precipitation was less accurate.

Our study was based on only one meteorological variable at one station, which is insufficient for accurate modeling and forecasting. Potential future work includes extending the analysis spatially to cover the entire island, using longer time series, and including other variables (such as temperature, pressure, evaporation, and humidity).

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