PREDICTION OF RAINFALL IN THE SOUTHERN HIGHLANDS OF TANZANIA

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ABSTRACT

Previous studies on the variability of March to May (MAM) and October to December (OND) rainfall in East Africa have mainly covered the whole region without considering the local climate zones such as the Southern Highlands of Tanzania. Results from the regional studies have shown that the Indian Ocean Dipole (IOD) and Outgoing Longwave Radiation (OLR) have strong association with OND rainfall and weak one with MAM rainfall in East Africa. The present study was aimed at determining the potential predictors for the MAM and OND rainfall by considering IOD, El Niño Southern Oscillation (ENSO), Quasi-biennial Oscillation (QBOu30 and QBOu50) and OLR. . Results suggest that rainfall in Southern Highlands of Tanzania is associated with IOD, ENSO, QBO and OLR. It is found through a Principal Component Regression that IOD, OLR and QBOu30 are potential predictors of both MAM and OND rainfalls. QBOu50 is a potential predictor for MAM and ENSO for OND rainfall, but as previous studies showed, ENSO is a weak predictor for MAM rainfall.QBOu50 is also a weak predictor for OND rainfall. It is therefore recommended that IOD, QBou30, OLR, QBOu50 and ENSO should be considered in rainfall forecasting in the Southern Highlands of Tanzania.

INTRODUCTION

Rainfall is an important parameter for crop production in the regions where irrigation is not developed. Rainfall variability in terms of amount and time leads to poor crop production because it affects the soil moisture. Variability in rainfall amounts leads to either too much rainfall which causes floods and water logging or very little rainfall resulting in inadequate soil water and moisture needed for crops to grow well. For example, the increase of rainfall above normal leads to a decrease in maize production due to too much water in the soil and nutrients being washed away by running water (Magehema et al. 2014).

A number of studies have been done to understand how different climate indices or rainfall drivers affect rainfall amounts and distribution at different places in the world. A study to investigate climate forcing in Australia showed that El Nino Southern Oscillation (ENSO) using Southern Oscillation Index (SOI), Indian Ocean Dipole (IOD) and Madden Julian Oscillation (MJO) have significant influence on rainfall in eastern Australia where by the variance explained by each index approached 50% (Risbey et al. 2009). In the Amazon basin, it was indicated that rainfall is correlated ($r = -0.6$) to Outgoing Longwave Radiation (OLR) (Liebmann et al. 1997).

The main rainfall seasons in East Africa are March to May (MAM) and October to December (OND). MAM is the long rains and most of the precipitations occur in this season and is the main crop production season in most parts of East Africa. The variability of OND rainfall season shows a greater intra-annual variability than MAM (Camberlin et al. 2009). A number of studies have been conducted to investigate how the climate indices influence rainfall. It has been observed that rainfall in East Africa is influenced by IOD and ENSO (Owiti et al. 2008). Few studies have been done to analyze rainfall variability in local climate zones. Climate is well understood when the study region is downscaled to local climate zones. This is important because some of the climate indices are regional and seasonal dependent (Hastenrath 1995, Ntale and Gan 2004). Inter − annual variability of OND seasonal rainfall in northern Tanzania was studied through a multiple regression model using QBO and SOI indices, the model explained about half of the OND rainfall variance (Kabanda and Jury 1999). QBO (using QBOu30 index) was found to correlate with rainfall in southern and western Tanzania (Ng'ongolo and Smyshlyaev 2010). The present study aimed at investigating the potential of QBO (using QBOu30 and QBOu50 indices), ENSO (using SO index), IOD (using DMI index) and OLR as rainfall predictors in the Southern Highlands of Tanzania.

MATERIALS AND METHODS
Monthly total rainfall data from 1979 to 2010 measured from the study zone (Fig. 1) was obtained from the Tanzania Meteorological Agency (TMA). The base period 1979-2010 was chosen in order to have at least 30 years rainfall data, the minimum period for judging the climate of a given region (WMO 2003). Four rain gauge stations used in this study were Iringa (1428 m above sea level and annual mean rainfall of 590 mm), Songea (1036 m above sea level and annual mean rainfall of 1057 mm), Mbeya (1758 m above sea level and annual mean rainfall of 913 mm) and Sumbawanga (1722 m above sea level and annual mean rainfall of 914 mm). ENSO was quantified by SOI monthly data, OLR monthly data was gridded at 2.5° x 2.5°, and QBO data at u30 and u50 standardized winds for the period 1979 - 2010 were obtained from the National Oceanic and Atmospheric Administration (NOAA)-National Centers for Environmental Predictions (NCEP) dataset. IOD was quantified by the Dipole Mode Index (DMI) monthly data for the period 1979-2010 and were obtained from Japan Agency for Marine-Earth Science and Technology (JAMSTEC).
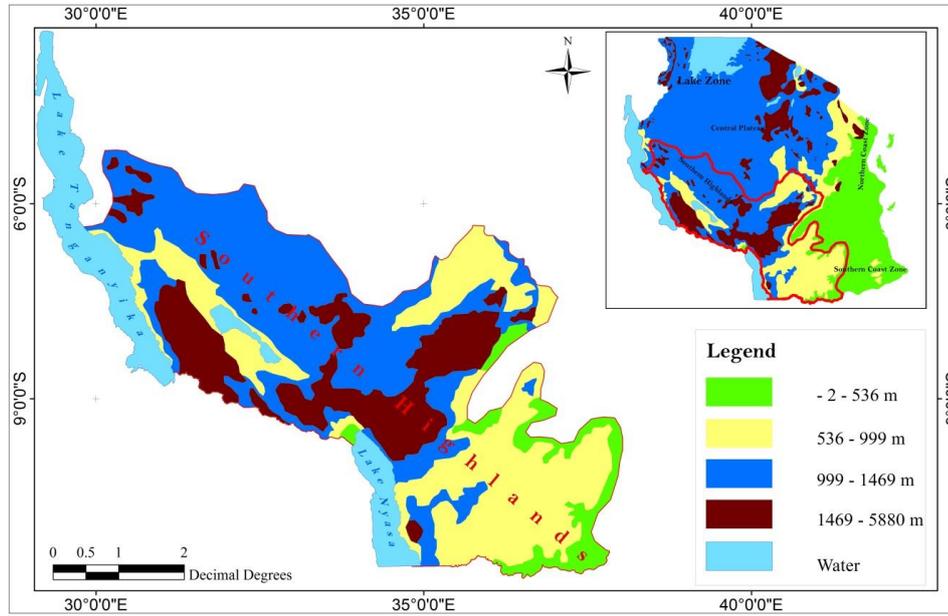
Figure 1: Map of the Southern Highlands of Tanzania. The insert is the map of Tanzania. (Source: GIS Lab Institute of Resource Assessment (IRA) – University of Dar es Salaam)

OND and MAM Rainfall Totals were computed for each rain gauge station. The JJAS, OND, DJF and ASOND Average Predictors were calculated (Table 1). Each Average Predictor Season contained columns, DMI, SOI, QBOu30, QBOu50 and OLR. The sixth column in each case is one of the Rainfall Totals mentioned above. Table 1 shows the Rainfall Totals versus Average Indices and the time lags/leads.

Table 1: Rainfall Totals and their Average Predictor Seasons

S/N	Rainfall Totals	Average Predictors	Time Lag/Lead
1	MAM	OND	3 time lag
		DJF	1 time lag
		ASOND	3 time lag
2	OND	JJAS	1 time lag
3	OND	FMA	6 time lag

Data were fitted to Multiple Linear Regression (MLR) model (1) and Principal Component Regression (PCR) model (2) (Haque et al. 2013) using MATLAB.

$$\mathbf{Y} = \mathbf{X}B_i + \mathbf{e} \qquad (1)$$
$$\mathbf{Y} = (\mathbf{PCs})B_i + \mathbf{e} \qquad (2)$$

where $\mathbf{Y} = (y_1, y_2, \dots, y_n)$ is a vector representing the dependent variable (OND

or MAM rainfall). B_i for $i = 0, 1, 2, 3, \ldots, r$ is a vector of model parameters with $r + 1$ rows for r-predictors and $\mathbf{X} = (x_1, x_2, \ldots, x_r)$ are predictors, then **X** will be an $n \times (r + 1)$ matrix of the predictor variables and $\mathbf{e} = (e_1, e_2, \ldots, e_n)$ is vector of residues with $n -$ rows.

PCR model is an MLR model in which the independent variables $\mathbf{X} = (x_1, x_2, \ldots, x_r)$ are transformed to a new set of low dimension and independent principal components (PCs) by using PCA. The dependent variable $\mathbf{Y} = (y_1, y_2, \ldots, y_n)$ is regressed on $\mathbf{X} = PC_i$ for $i = 1, 2, \ldots, r$. The models (1) and (2) and the statistics associated with it assume that the data is normally distributed. In this paper the Anderson – Darling (AD) Test (Saculinggan and Balase 2013) was used to test for normality. AD Test was implemented in MATLAB, if $h = 0$ the H_o: null hypothesis that Y is normally distributed is not rejected and for $h = 1$ the H_o is rejected in favour of H_a: the alternative hypothesis that Y is not normally distributed. Data which was not found to be normally distributed was transformed by using natural log transformation (Mainardi 2010). Correlation between rainfall and climate indices and the m ulticollinearity of the climate indices were determined in MATLAB.

Model performances were evaluated by using Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Square Error (MSE). The correlation coefficient r between the predicted and observed rainfall and the coefficient of determination R^2 were calculated. R^2 shows the amount of variance in the dependent variable which is explained by the model, but for a linear model with more than one explanatory variable, R^2 adjusted is used because it takes into account of all the predictors in the model. R^2 and R^2 adjusted ranges from 0 to 1; a value of 1 indicates a perfect fit. The RMSE has been employed as a standard measure of model performance in

meteorology and MAE is a widely used tool in model evaluation because it is a natural measure of average error (Willmott and Matsuura 2005). A model which generalizes better will have low MSE, MAE and RMSE; a value of zero (ideal value) indicates a perfect fit. For a parsimonious model the MSE during training and MSE during validation are same in order of magnitude. (Chai and Draxler 2014)

The RMSE, MSE, MAE, R^2 and R^2 adjusted are computed as follows:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \quad (3)$$

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \quad (4)$$

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \quad (5)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \quad (6)$$

$$R^2 - \text{adjusted} = 1 - \frac{\text{SSE}/(n - q - 1)}{\text{SST}/(n-1)} \quad (7)$$

Where $y_i =$ Observed value, $\hat{y}_i =$ predicted value, $\bar{y} =$ mean value of y, N = Sample size or Number of observations, n = Total number of observations, q = Number of regression coefficients, including the intercept, SSE = Sum of squared Error and SST = Sum of Squared Total (Bennett 2013).

RESULTS AND DISCUSSION
Pearson Correlations coefficients between rainfall and climate indices are shown in Table 2. PCR models for MAM rainfall with ASOND indices and OND rainfall with FMA indices were significant in Iringa only, this is why there are fewer predictors in Mbeya, Songea and Sumbawanga. Some of the correlation coefficients between rainfall and climate indices are insignificant, but results of PCR model (2) indicated that these climate indices are potential predictors of rainfall in the study zone. This is because the Pearson correlation r does not take into account the complexity present in the data. In the presence of curvilinear, collinearity and/or multicollinearity (Table 3), the

Pearson correlation, r, does not give the true relationship between the predictor and the dependent variable (Krahaet al. 2012). The Coefficient of determination R^2-adjusted will also be affected because it is just the sum of the squares of the Pearson correlation r. R^2-adjusted will be smaller in most cases than expected (Mason et al. 1991), the same will happen if curvilinear relationships exits.

Table 2: Correlation between Climate indices and Rainfall (* Significant values at 5 % significance level and bolded values approach the significance level)

Iringa		Individual Climate Indices Considered				
Correlation Between:		DMI	SOI	QBOu30	QBOu50	OLR
MAM Total Rainfall	OND Indices	0.26	0.1	0.15	-0.06	-0.01
MAM Total Rainfall	DJF Indices	0.41*	0.06	0.26	0.05	0.03
MAM Total Rainfall	ASOND Indices	0.22	-0.01	0.12	-0.09	-0.01
OND Total Rainfall	JJAS Indices	0.42*	-0.37	0.18	0.18	-0.27
OND Total Rainfall	FMA Indices	0.01	0.41*	0	-0.09	**0.32**
Mbeya		Individual Climate Indices Considered				
Correlation Between:		DMI	SOI	QBOu30	QBOu50	OLR
MAM Total Rainfall	OND Indices	-0.03	**0.31**	-0.14	-0.23	**0.3**
MAM Total Rainfall	DJF Indices	-0.01	**0.33**	-0.03	-0.19	**0.38**
OND Total Rainfall	JJAS Indices	0.12	-0.24	0.17	0.24	-0.16
Songea		Individual Climate Indices Considered				
Correlation Between:		DMI	SOI	QBOu30	QBOu50	OLR
OND Total Rainfall	JJAS Indices	0.2	-0.25	0.14	0.19	-0.14
Sumbawanga		Individual Climate Indices Considered				
Correlation Between:		DMI	SOI	QBOu30	QBOu50	OLR
MAM Total Rainfall	OND Indices	-0.21	**0.35**	-0.11	-0.03	**0.34**
MAM Total Rainfall	DJF Indices	-0.13	0.29	-0.13	-0.09	0.40*
OND Total Rainfall	JJAS Indices	**0.34**	-0.27	-0.14	-0.11	-0.11

The predictors entered the models (1) and (2) were considered significant if the p – values are such that $p \leq 0.05$. Predictors that entered MLR and PCR models (Table 4) differ due to collinearity between the indices (Table 3). Most of the climate indices are significantly correlated to each other (Table 3). It is observed here that even the insignificant collinearity has a considerable effect on the significance or insignificance of the predictors entering the model (Tu et al. 2005). RMSE, MSE and MAE were used to evaluate the performances of PCR and MLR models, PCR models was found to have lower RMSE, MAE and MSE values as compared to MLR model. By this reason the predictors entered the PCR model are taken as the potential predictors for the MAM and OND rainfall in the southern highlands of Tanzania because the collinearity effect has been reduced by the application of PCA.

Table 3: Collinearity between Climate Indices Used in this Study

	OND Indices					DJF Indices				
	DMI	SOI	QBOu30	QBOu50	OLR	DMI	OLR	QBOu30	QBOu50	SOI
DMI	1	-0.53*	0.38*	0.4*	0.59*	1	-0.38*	0.11	0.39*	-0.3
SOI	-0.53*	1	-0.22	-0.15	0.87*	-0.4*	1	-0.07	-0.18	0.78*
QBOu30	0.38*	-0.22	1	0.78*	-0.23	0.11	-0.07	1	0.62*	-0.1
QBOu50	0.4*	-0.15	0.78*	1	-0.14	0.39*	-0.18	0.62*	1	-0.3
OLR	-0.59*	0.87*	-0.23	-0.14	1	-0.3	0.78*	-0.09	-0.32	1

	JJAS indices					ASOND Indices				
	DMI	SOI	QBOu30	QBOu50	OLR	DMI	SOI	QBOu30	QBOu50	OLR
DMI	1	-0.59*	0.07	0.02	-0.47*	1	-0.6*	0.33	0.31	-0.6*
SOI	-0.59*	1	-0.17	-0.02	0.87*	-0.6*	1	-0.22	-0.08	0.89*
QBOu30	0.07	-0.17	1	0.79*	-0.25	0.33	-0.22	1	0.8*	-0.3
QBOu50	0.02	-0.02	0.79*	1	-0.12	0.31	-0.08	0.8*	1	-0.1
OLR	-0.47*	0.87*	-0.25	-0.12	1	-0.6*	0.89*	-0.25	-0.13	1

	FMA Indices				
	DMI	SOI	QBOu30	QBOu50	OLR
DMI	1	-0.08	-0.22	-0.02	-0.08
SOI	-8	1	0.09	-0.05	0.7*
QBOu30	-0.22	0.09	1	-0.02	0.15
QBOu50	-0.02	-0.05	-0.02	1	0.06
OLR	-0.08	0.7*	0.15	0.06	1

Table 4: Summary of Predictors entered MLR and PCR models for MAM and OND rainfalls.

Rainfall	Model	Potential Predictors				
		OND	DJF	ASOND	JJAS	FMA
MAM	MLR	DMI, SOI, QBOu50, QBOu30,	OLR, QBOu30, QBOu50, DMI			
	PCR	QBOu50, SOI, OLR	DMI, QBOu30, QBOu50, OLR	OLR, QBOu50		
OND	MLR				SOI, QBOu30, DMI, OLR, QBOu50	QBOu50, QBOu30, OLR
	PCR				OLR, SOI, DMI, QBOu30,	DMI, SOI, QBOu30,

IOD (JJAS DMI index) has positive correlation coefficient of $r = 0.12$ to $r = 0.42$ with OND rainfall in Southern Highlands of Tanzania. Past studies showed that OND rainfall is positively highly correlated with DMI and Niño 3.4 in East Africa but no information on the lag or lead time used was provided (Diem *et al.* 2014). MAM rainfall in Southern Highlands of Tanzania has positive correlation coefficient from $r = 0.22$ to $r = 0.41$ in Iringa and changes to negative as you move towards Mbeya and Sumbawanga where it ranges from $r = -0.03$ to $r = -0.13$. In Table 3

we note that DMI from both OND and DJF indices are significantly correlated to other indices, this may have influenced the significance or insignificance of the correlation coefficients (Tuet al. 2005). The PCR models for which the collinearity has been reduced by PCA in Iringa, Mbeya, and Sumbawanga were significant with p-values of 0.002, 0.016 and 0.026 respectively. This implies that IOD is a potential predictor of both MAM and OND rainfall in Southern highlands of Tanzania. Past studies indicated that IOD has high influence on OND rainfall in East Africa than MAM (Behera 2005).It is noted also that rainfall in southern highlands of Tanzania depends on the sea surface temperatures (SST), warmer SST over the western Indian Ocean brings rainfall and the cool SST results in less rainfall (Mbululo and Nyihirani 2012).

FMA average SOI has positive correlation of $r = 0.41$ with OND rainfall in Iringa. JJAS averaged SOI has negative correlation of $r = -0.24$ to $r = -0.37$ with OND rainfall in the study zone. In the present study SOI is found to be the potential predictor for OND rainfall but is less important predictor for MAM rainfall in southern highlands of Tanzania. This is in agreement with the past studies (Ng'ongolo and Smyshlyev 2010).

Two QBO indices were used in this study; QBOu30 and QBOu50, correlation coefficients of each with MAM or OND rainfall are shown in Table 2. OND rainfall shows positive correlations (except in Sumbawanga where it has negative correlation) values with JJAS averaged QBOu30 index while MAM rainfall has negative correlation values with DJF, OND and ASOND averaged QBOu50 index. Results of the PCR model indicate that QBOu30 and QBOu50 are potential predictors for MAM rainfall. This is because QBOu30 and QBOu50 are highly correlated (Table 3) which may result in overlapping

variance and hence wrong interpretation (Yoo et al. 2014) if only one of the two is used in rainfall prediction.

FMA averaged OLR has correlation of $r = +0.32$ with OND rainfall in Iringa. MAM rainfall is positively correlated ($r = 0.34$ to $r = 0.40$) with OLR from Sumbawanga to Mbeya and correlation decreases towards Iringa. Earlier studies reported negative OLR values of $-15\,W/m^2$ to $-20\,W/m^2$ over the Tanzanian coast and during El Nino, negative OLR anomalies move towards the west over the western Indian Ocean during the OND seasons (Kijazi and Reason 2005), these values are indicative of deep convection and hence results in high rainfall. In this study it has been shown that OLR is a potential predictor of both OND and MAM rainfall in the southern highlands of Tanzania. In Nigeria OLR was one of the predictors and found to have correlation of $r = 0.32$ to $r = 0.62$ with JJAS rainfall (Omogbai 2010). In central and tropical Pacific, the inter-annual variability in rainfall close to equatorial areas was found to be highly correlated ($r = 0.72$) with Convective Coupled Mixed Rossby – Gravity waves activity which are determined by OLR (Horinouchi 2012). This indicates that rainfall in near equatorial tropics and even subtropical regions is correlated with OLR. OLR is the proxy for convective rainfall (Lyons 1991, Liebmann et al. 1998) in near equatorial regions like the Southern highlands of Tanzania.

Explained rainfall variance (R^2- adjusted) by PCR model and the correlation coefficient r between observed and predicted rainfall are shown in Table 5. The maximum explained variance is R^2- adjusted $= 0.44$. This suggests two things; one is that rainfall in Southern highlands of Tanzania has both linear and nonlinear relationships with the climate indices considered in this study. The nonlinear relationships accounts part of the

unexplained variance because MLR and PCR models are linear and cannot capture nonlinear relations present in the data (Sarani et al. 2012). The second thing is that there exist other processes and factors that contribute to the rainfall variability and distribution in southern highlands of Tanzania and over the whole region of East Africa in general.

Table 5: Correlations between Observed Rainfall and Predicted rainfall by PCR Model

	Season/ IndicesUsed/Model		Observed Rainfall		Rain Station
			MAM	OND	
Predicted Rainfall	MAM-PCR	DJF	r = 0.61 R^2 adj = 0.37		Iringa
		OND	r = 0.52, R^2 adj = 0.27		
		ASOND	r = 0.55, R^2 adj = 0.30		
		DJF	r = 0.49, R^2 adj = 0.24		Sumbawanga
		DJF	r = 0.40, R^2 adj = 0.16		Mbeya
		OND	r = 0.57, R^2 adj = 0.32		
	OND - PCR	JJAS		r = 0.35, R^2 adj = 0.12	Songea
		JJAS		r = 0.66, R^2 adj = 0.44	Mbeya

Such other processes and factors are for example, topography; the study zone is a highland with a series of topographical features like mountain ranges and peaks, plateaus and water bodies which modify rainfall distribution and amount (Ogwang et al. 2014). These features shape the rainfall distribution by altering the distribution of local winds and the condensation of precipitable water. Highlands enhance forced convection which can result in rainfall. Moisture transport and surface heat flux, moisture convergence (rainfall increased) or divergence (rainfall decreased) are influenced by topographical features. High frequency mesoscale and sub-synoptic disturbances are generated by highlands (Slingo et al. 2005, Hession and Moore 2011, Ntwali et al. 2016). Topography influences rainfall distribution in all over the globe, for example in Sweden the highest annual rainfall is observed in the Scandinavian mountain ranges (Johanson and Chen 2003). Other factors include perturbation in the wind field which is responsible for governing the horizontal motion and moisture gradients. The wind field includes equatorial westerlies, northeast trade winds and southeast trade winds. The convergence of north easterlies and easterlies during November leads to an increase in moisture towards Tanzania and brings rainfall. Much rainfall occurs when equatorial westerlies are not strong enough

to export much of the equatorial moisture far away from east African countries (Mapande and Reason 2005). Other processes that bring rainfall in Tanzania are the position and movements of the ICTZ, the easterly and westerly wave disturbances, tropical cyclones and subtropical anticyclones and mesoscale systems (Mahongo and Francis 2012).

convective mesoscale and planetary scale systems. Most of the rainfall in tropics falls from the cumulus clouds; rainfall is organized from convective mesoscale systems to planetary scale systems like MJO. These systems are driven by Convectively Coupled Equatorial Waves (CCEWs) like Kelvin waves, Equatorial Rossby waves, Mixed Rossby-Gravity waves and zonal Inertio-Gravity waves (Kiladis et al. 2009, Marques and Castanheira 2015).

CONCLUSION AND RECOMMENDATIONS

In this study, RMSE, MAE, MSE, Pearson correlation, R - square and R-square adjusted were used to evaluate model performance, Significance was attained for a p-values less than 0.05 significance level. The study aimed at investigating the potential of IOD, ENSO (using SOI index), QBOu30, QBOu50 and OLR in predicting rainfall in the southern highlands of Tanzania. DJF, OND, JJAS, ASOND and FMA average climate indices were considered. Results have shown that IOD, SOI, QBOu30, QBOu50 and OLR are potential rainfall predictors for the Southern highlands of Tanzania. IOD and QBOu30 are found to be potential predictors of both MAM and OND rainfall, QBOu50 is potential predictors of MAM but a weak predictor for OND rainfall.

Therefore it is recommended to consider these climate indices in rainfall forecasting in southern highlands of Tanzania and the

use of PCR model to reduce collinearity in the data. The amount of variance explained could be maximized by the use of nonlinear methods and models. Also by considering other ENSO indices like Nino 3 and Nino 3.4; other meteorological parameters like Relative Humidity (RH), temperature, wind in the lower and upper levels and solar radiation together with altitude are recommended in future studies.

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