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Determinants of Seasonal Rainfall And Forecast Skills in Semi-arid South-east Kenya

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Abstract

Determination of seasonal rainfall predictors with local ramification offers an opportunity to improve climate forecast. This study makes a contribution towards meeting the challenges of more local level studies by identifying sea surface temperatures influencing seasonal rainfall and forecast skill for the main growing season of October-December in southeast Kenya. The study was based on nine key rainfall stations located in different climatic zones in southeast Kenya, and used monthly rainfall for the period 1961-2003. Stepwise regression results show that sites in southeast Kenya are influenced by different SSTs, with the southern oscillation index and the Atlantic Ocean emerging as key seasonal rainfall predictors. Niño1, Niño3.4, Niño3 and Niño4 SSTs subsequently emerged as predictors in the region. Forecast verifications scores generated from *Climlab2000* software show a significant association between observed and forecast seasonal rainfall for six out of the nine stations. Stations with a higher hit score skill also showed a significant correlation between observed and predicted rainfall. Sites in semi-arid environment (UM4 and LM5) had the highest skill of predicting dry events, while high altitude zone (LH2) had the highest skill of predicting wet events.

Key words: *rainfall determinants, forecast skill, southeast Kenya*

Introduction

Climate variability has posed a threat to climate-dependent economic sectors such as agriculture and forestry, and significantly contributes to environmental degradation on a global scale (Chipanshi et al., 2003). Developing countries, particularly in sub-Saharan Africa, have to contend with the disproportionate effects of climate variability. For many of these countries, agriculture is the mainstay of their economies and accounts for between 20-30% of their GDP (Sokona & Denton, 2001). A large part of agriculture in developing countries is dependent on rainfall, and any climate variability affects food production and livelihoods, and consequently

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exposes a plethora of social and economic problems that remain hidden during a normal rainy season.
It was against this background that prior to the 1997/98 El Niño event, the international community established the Regional Climate Outlook Forums (RCOFs) (WMO, 2001) in developing countries. RCOFs were designed to provide advance information on the likely climatic features of the upcoming season, and have significant applications in agricultural management. However, tropical climate prediction remains a great challenge (Hastenrath et al., 2004). One of the challenges is when forecast information covers a wide geographic area (Patt & Gwata, 2002; Lemos et al., 2002). That is, when the information covers an entire country or a region it is unclear of local ramifications. It is on the understanding that rainfall patterns are very heterogeneous over a small area that this study seeks to make a contribution towards meeting the challenges of more local level studies by identifying sea surface temperatures (SSTs) influencing seasonal rainfall and determine the skill of forecasting in semi-arid southeast Kenya.

a) The study area

The southeast Kenya is a subset of Kenya's arid and semi-arid lands (ASAL). The region falls on the eastern side of Mount Kenya. The area is divided into eight administrative districts as shown in Fig. 1. The area has two rainy seasons: the long March-May (MAM) rains, and the short October-December (OND) rains. Precipitation is unevenly distributed within the rainy season, and shows significant variability from year to year and season to season. According to Jaetzold and Schmidt (1983), southeast Kenya has several agro-ecological zones, ranging from high rainfall/high productivity sites (annual precipitation>1000, upper highlands) to areas of extremely low productivity where rainfall is sparse and variable (annual rainfall <700mm, lower midlands). Northern districts (Meru North, Meru Central, Meru South and parts of Embu) border Mt. Kenya and form the leeward side. These districts have high potential agro-ecological zones such as lower highland (LH) and upper midland (UM), and receive good rainfall for tea and coffee farming. South and eastern districts of the sub-region are on the other hand characterized by highly variable rainfall with short growing season and livestock keeping. Lower midland (LM) 5 is the largest agro-ecological and falls within the southeastern districts (Kitui, Mwingi, Machakos, Makueni).

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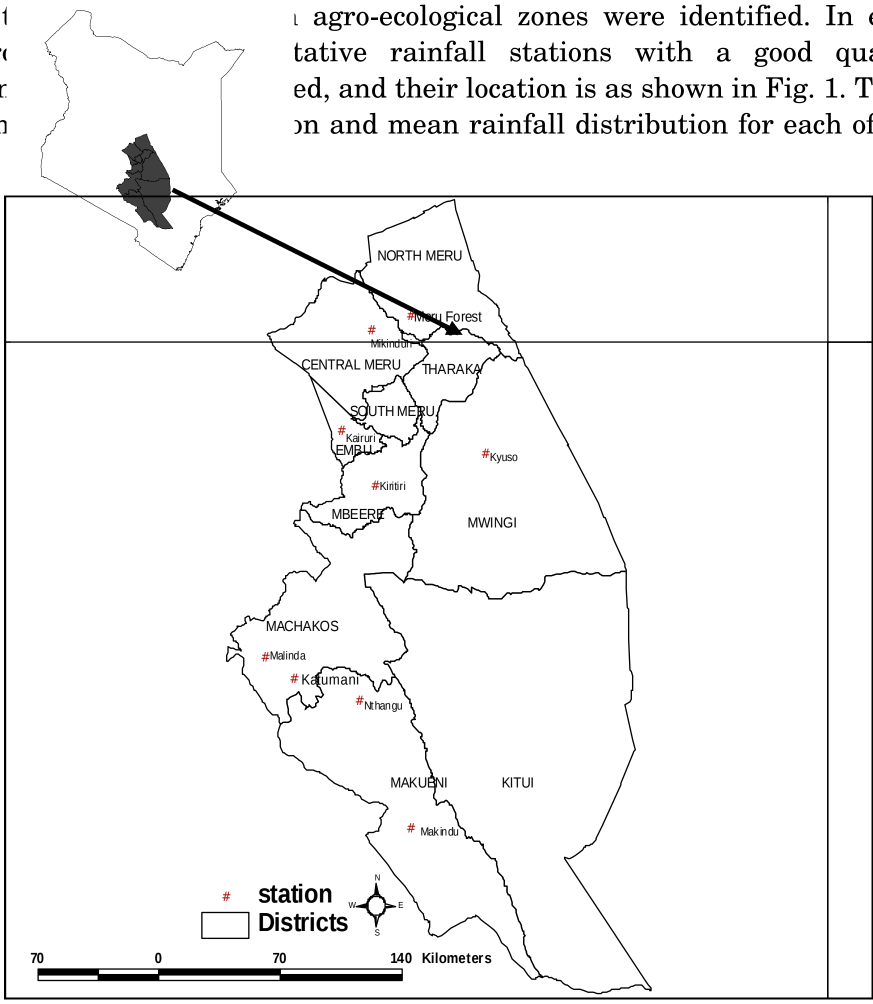

stations.

Figure 1: ***Map showing administrative districts and rainfall stations in the study area in Kenya***

Table 1: Geographic location, agro-ecological zones and means rainfall distribution

Station	Rainfall Data (No. of years)	AEZ	Altitude (m)	Rainfall (mm)		
				MAM	OND	Annual
Nthangu	41	LH2	1829	453.1	538.	1188.7

					1	
Kairuri	38	UM2	1676	793.5	563.1	1672.7
Mikinduri	29	UM3	1158	876.8	990.1	2028.8
Katumani	42	UM4	1600	276.6	299.9	696.0
Malinda	34	UM5-6	1524	243.0	180.1	549.4
Meru Forest	42	LM3	1585	538	772.4	1476.7
Kiritiri	42	LM4	1143	440.1	425.5	963.5
Makindu	42	LM5	1000	200.1	338.3	629.3
Kyuso	42	LM5	747	282.5	418.1	779.2

Note: Most of the stations receive more OND rainfall than MAM rainfall. All the stations had rainfall data of more than 25 years. AEZ = Agro-ecological zone

b) Rainfall prediction in Eastern Africa

Rainfall climatology in eastern Africa has been found to correlate with sea surface temperatures over equatorial Indian Ocean, eastern Pacific Ocean, SOI, Tropical cyclones, ITCZ, and anti-cyclones. Ogallo (1988) found peak lag correlation coefficient r, of -0.6 between SOI and October-December rainfall a long the coast of southern Kenya and northern Tanzania. Farmer (1988) recorded similar findings, establishing a correlation between SOI and the short rains of the Kenya coast. Hutchison (1990) established a coefficient of correlation r of -0.8 between the (OND) seasonal rainfall and SOI in southern and central Somalia. Shisanya (1996) computed month-month patterns of zero-lag correlation for some stations in southeast Kenya between OND rainfall and SOI, and found the correlation to be significant ($p<0.05$). But SOI is not the only predictor of southeast Kenya rainfall. Phillips and McIntyre (2000) found a correlation coefficient, r, 0.57 between NINO3 region SST anomalies of July-September (JAS) and September-December rainfall in Uganda. According to Mutai et al. (1998), variability in equatorial Pacific SSTs is the lead predictor of east Africa's OND rainfall, with equatorial Indian Ocean and southern Atlantic Ocean surface temperatures playing a smaller although a significant role. A study by Hastenrath et al. (2004) found SST indices and tropospheric winds within the equatorial Indian Ocean to influence east Africa's coastal OND-rains. Nonetheless, the correlation was found to be deteriorating particularly in the 1980s and 1990s. Anyamba et al. (2001) found a significant ($p<0.05$) zero lag correlation between East Africa's NDVI and southern Atlantic, Global Tropics SST, Eastern Pacific Wind Index (EPWI) and Western Indian Ocean (WIO) SST index. In Kenya, the International Research Institute for Climate and Society (IRI) (2005) conducted a demonstration project in application of seasonal climate information to promote a predictable supply of water for both power supply and irrigation. The IRI study identified dominant predictors influencing April-July (AMJJ) and October-December (OND) inflows of Masinga dam, a hydroelectric power station.

The point of focus in all these studies was OND rains. Two reasons explain this. October-December rains have shown a significant relationship with ENSO signals (Farmer, 1988; Hutchison, 1990), unlike the MAM rains in which there is agreement in literature that it has no significant relationship with ENSO (Mutai et al., 1998; Phillips & McIntyre, 2000). Secondly, OND rains have been found to be most coherent and predictable (Odingo et al., 2002). Thus the OND season has proved to be the main growing season for farmers in southeast Kenya. This study, therefore, examines the specific SSTs influencing OND rainfall in southeast Kenya and the forecast skill of each of them.

2. Data and Methods of Study

2.1 Data

2.1.1 Rainfall

Monthly mean rainfall records (1961-2003) for a network of nine stations in the southeast Kenyan region were used in this study (Fig. 1; Table 1). Although the region has 23 rainfall stations with daily data, only nine were sampled on the basis on data quality. The nine sample stations had daily data with less than 10% missing values in any given year. Selected rainfall stations had data ranging between 29 and 42 years. According to Atheru (1999), 25 year data are the minimum to get a reliable estimate of forecast. Estimation of missing data was done as described by Shaw and Wheeler (1985), while F-test (Alders & Roessler, 1977) was used to test data homogeneity.

2.1.2 Sea Surface Temperatures (SSTs) Indices

A time series of monthly SST data from 1961-2003 was used to develop OND rainfall forecast model for all the 10 rainfall stations. ENSO indices used in the study were:

1. SSTs anomaly data drawn from the NIÑO3.4 region in the eastern Pacific Ocean (5°N-5°S; 170-120°W)
2. SSTs anomaly data drawn from the NIÑO4 region in the eastern Pacific Ocean (5°N-5°S, 160° E-150° W)
3. SSTs anomaly data drawn from the NIÑO1 region in the eastern Pacific Ocean

4. SSTs anomaly data drawn from the NIÑO3 region in the eastern Pacific Ocean (5° N-5° S, 150°W-90°W)
5. Southern oscillation index (SOI) - Represents the basin-wide sea-saw in atmospheric pressure patterns between the eastern and western Pacific, measured as normalized difference in sea level pressure between Tahiti and Darwin, Australia.
6. North Atlantic SST (NAT) located 5-20°N, 60-30°W
7. South Atlantic SST (SAT) located 0-20°S, 30°-10°E
8. Global Tropics SST (TROP) located 10°S-10°N, 0-360°

These data were obtained from the NOAA, National Weather Service, National Centers for Environmental Prediction, Climate Prediction Centre (http://www.cpc.noaa.gov/data/indices/). Use of SSTs in establishing their influence on seasonal rainfall is also found in Verdin et al. (1999), Phillips and McIntyre (2000), and Seleshi and Zanke (2004). Since the determination of forecast skill focused on OND growing season, this study utilized SSTs of the months of June to September (JJAS) on the assumption that these are the SSTs influencing October- December rainfall in southeast Kenya.

a) Statistical analysis

Rainfall data was subjected to forward stepwise regression (using SYSTAT software) to identify rainfall predictors for individual stations. In selecting predictors, a maximum of six predictors was considered to avoid over-fitting of the forecast model that sometimes lead to inaccuracy. A step with an improved coefficient of determination (r^2) value with a near 0 p-value was picked and a regression equation generated using equation 1. Data for each station was regressed at 85% confidence level after the 95% confidence limit failed to yield results.

$$Y_i = a + b_1 x_1 + b_2 x_2 + \dots\dots\dots b_n x_n + e \qquad \dots\dots\dots\dots\dots\dots\dots 1$$

Equation 1 was also used to estimate missing daily rainfall data. Distribution approach, contingency tables and associated scores (Brooks & Doswell, 1996; Atheru 1999) were used to determine forecast skill for the short rains of the study area. The advantage of the distribution approach is that the nature of the forecast errors can more easily be diagnosed. The disadvantage is that it is more difficult to condense the results into a single number. In this study there were three categories in the contingency tables: below normal, normal and above normal forecasts.

Normalized observed and forecast rainfall data values were imported from MS Excel to the *Climlab2000* computer software for analysis (using contingency tables). CLIMLAB2000 is climate data analysis and visualization software that has been developed by the International Research Institute for Climate Prediction (IRI) for training climate prediction models (Mutemi, 1999). Contingency tables of 3 × 3 with chi-square set at 95% level gave results in the order of lowest values (below normal), near zero values (normal) and highest values (above normal). To calculate forecast verification scores, contingency table values were used as discussed by Murphy (1993) and Atheru (1999).

Discussion of Results

Stepwise regression results show that October-December rainfall in southeast Kenya is influenced by various climate indices. Table 2 shows the determinants of seasonal rainfall for each of the stations. The Southern Oscillation Index (SOI) was the most common indice, emerging as one of the predictors in all but Meru Forest station. In two stations (Malinda and Kiritiri), SOI indices of more than one months (June, July and September) were the predictors. The correlation between between SOI and OND rainfall in eastern Africa is also reported in Ogallo (1988), Hutchison (1990), and Phillips and McIntyre (2000). The Southern (SAT) and Northern Atlantic (NAT) SSTs were predictors in three and two agro-ecological zones respectively. It is notable that stations influenced by the southern Atlantic SSTs fall north of the Equator(Meru Forest, Kiritiri and Kyuso), while those influenced by northern Atlantic SSTs are south of the Equator (Nthangu and Katumani). The influence of SAT on east African rainfall is discussed by Mutai (1998), and on NDVI by Anyamba et al. (2001). Camberlin et al. (2001) and Paeth Hense (2004) have demonstrated how SST anomalies within the Atlantic Ocean influence decadal and longer-term rainfall fluctuations along the West African coast and the Sahel zone. Global Tropical SSTs (TROP) are rainfall predictors at Kangundo rainfall station.

Table 2: Rainfall predictors for the nine sampled sites in southeast Kenya

Station	Predictor 1	Predictor 2	Predictor 3	Predictor 4	Predictor 5	Predictor 6
Nthangu	Niño3.4-June	SOI-Sept	NAT-Sept	Niño3.4-Sept	-	-
Kairuri	Niño1-Sept	SOI-June	-	-	-	-
Mikinduri	SOI-June	-	-	-	-	-
Katumani	NAT-June	SOI-Sept	-	-	-	-
Malinda	Niño3-Sept	SOI-June	SOI-July	-	-	-
Meru Forest	SAT-June	-	-	-	-	-

The influence of TROP SSTs on eastern African NDVI and rainfall are also reported in Anyamba et al. (2001) and Seleshi and Zanke (2004). Other SSTs infuencing seasonal rainfall in the southeast Kenya stations are Niño1 (Kairuri and Kiritiri), Niño3 (Malinda) Niño3.4 (Nthangu), and Niño4 (Kyuso). Studies by Verdin et al. (1999), Phillips and McIntyre (2000) Wannebo and Roseinzweig (2003) and Seleshi and Zanke, 2004) have discussed the influence of Niňo3 on NDVI and climate variability. In the selected stations of southeast Kenya, Niňo3 is a determinant of seasonal rainfall in agro-ecological zone 5-6 (a transition zone). Niňo1 is a determinant in the upper midland and lower midland zone while Niňo 3.4 and Niño4 are determinants in agro-ecological zones lower hihglands and lower midlands respectively. With the exception of Seleshi and Zanke (2004) and Anyamba et al. (2001), most of the literature avalable utilized only one of the SSTs and none explored the possibility of Niño1, Niño3.4 and Niño4 as rainfall predictors. Although Anyamba et al. (2001) utilized several SSTs, the study used one station in east Africa; while Seleshi and Zanke (2004) study was based in Ethiopia. Thus the present study contributes towards identifying rainfall determinants in the semi-arid region of Kenya.

Fig. 2(a), (b) and (c) are the cross validated forecasts generated from the predictors identified in Table 2 for three station (Katumani, Mikinduri and Makindu respectively). The stations represents agro-ecological zones Upper midland 4(UM4), Upper midland 3 (UM3) and Lower midland 5(LM5) respectively.

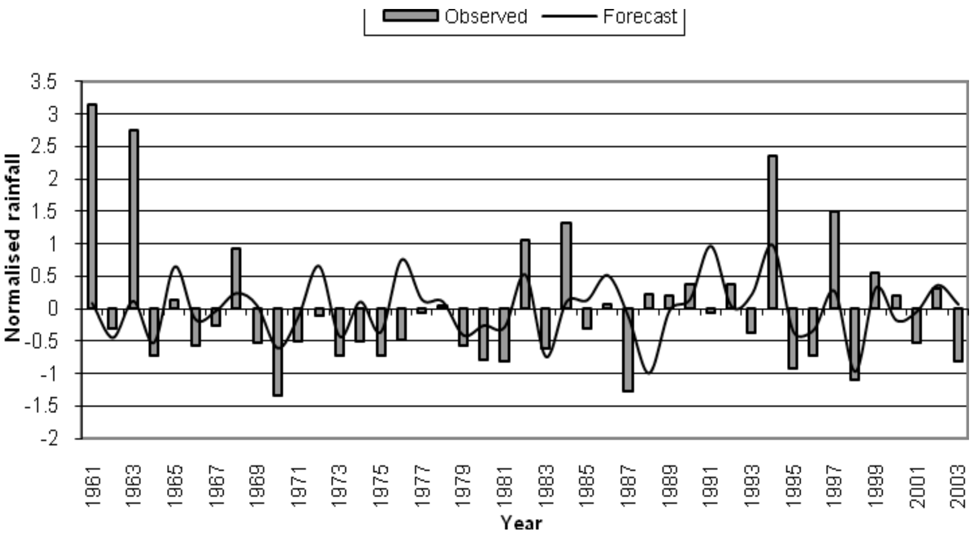

Figure 2 (a): Katumani

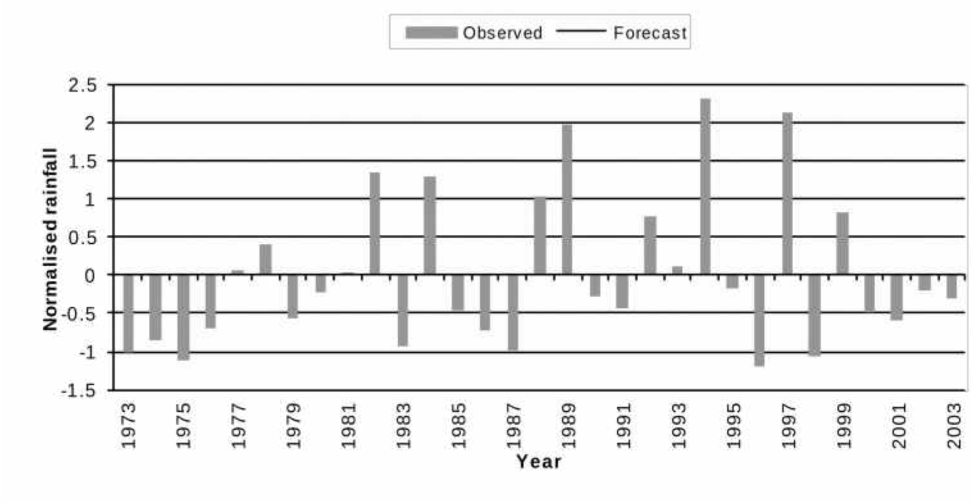

Figure 2 (b): Mikinduri

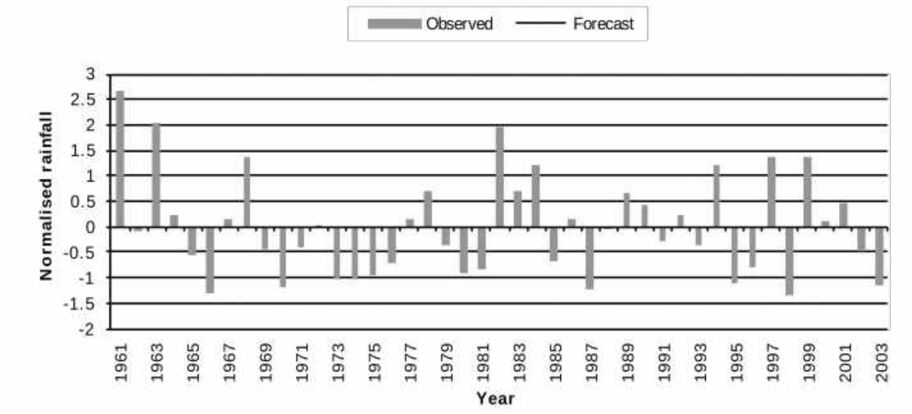

Figure 2 (c): Makindu

Figure 2: ***October-December observed and predicted rainfall for (a) Katumani (b) Mikinduri and (c) Makindu rainfall stations***

Table 3 presents the stepwise regression results between observed rainfall and SSTs, and forecast verification scores of stations in southeast Kenya. It is observed that Kiritiri and Nthangu had the highest coefficient of determination (r^2). The r^2 for these sites were 0.445 and 0.389 for Kiritiri and Nthangu respectively; an indication that SSTs explain 44.5% and 39% of the rainfall recieved respectively. In the rest of the stations, SSTs accounted for less than 30% of the rainfall received. Despite the low value of r^2, forecast verification scores show that with the exception of Kairuri, Meru Forest and

Table 3: Stepwise regression results and forecast verification scores

Station	R2	p-value	Percent Correct	Post agreement Dry (%)	Post agreement wet (%)	Hit Score Skill	X2
Nthangu	0.389	0.001	54.76	57	71	0.32	17.4*
Kairuri	0.272	0.003	35.90	31	46	0.04	2.31
Mikinduri	0.184	0.016	58.06	60	64	0.37	9.57*
Katumani	0.205	0.010	58.14	79	53	0.37	21.84*
Malinda	0.351	0.003	57.14	50	58	0.36	10.68*
Meru Forest	0.063	0.104	41.86	38	44	0.13	1.79
Kiritiri	0.44	0.001	58.14	57	67	0.37	13.25*

Kyuso, all the other stations have a better skill of forecast. It is observed in Table 3 that besides having low r^2, the three stations had the lowest forecast verification scores and the relationship between observed and predicted OND rainfall was not significant. Results for Mikinduri are, however, interesting; that despite having an r^2 of 0.184, the station's rainfall showed good verification scores, including the significant relationship between observed and predicted OND rainfall.

Stations in agro-ecological zones UM4 (Katumani), LM4 (Kiritiri) and UM3 (Mikinduri) had the highest percent correct (fraction of forecasts that were correct) values. Katumani, Makindu and Mikinduri had a skill of predicting dry events with a percentage of 79%, 64% and 60%, respectively. With the exception of Mikinduri, Katumani and Makindu fall in agro-ecological zones UM4 and LM 5 zones charaectirized by frequent climate variability. Wet events were best predicted at Nthangu (71%), Kiritiri (67%) and Mikinduri (64%). Nthangu and Mikinduri falls in agro-ecological zones LH2 and UM3, and recieve annual rainfall exceeding 1000mm while Kiritiri is in agro-ecological zone LM4 and recieves annual rainfall of over 900mm. The Hit score skill (Heidke skill score) measures the fraction of correct forecast, most often associated with chance as the standard of comparison and is a popular verification statistics (Atheru, 1999). The highest Hit Score values were recorded Mikinduri, Kiritiri and Katumani (0.37). Chi-sqaure (X^2) test results show that stations that had an above average percent correct values had forecast models showing a significant association between observed and forecast OND rainfall. The significant association is a demostration that SSTs of the eastern Pacific and Atlantic Oceans influence rainfall in southeast Kenya.

Conclusion

October-December rainfall in the southeast sub-region is influenced by across section of SSTs, and the southern oscillation index (SOI) is a key determinant. Variations in the SSTs influencing OND seasonal rainfall within the sub-region is a manifestation that rainfall patterns are heterogenous over a small physical area. Despite SSTs accounting for less than 50% of the OND rainfall received in the area, the significant association between observed and forecast rainfall in six stations is a cause for optimism.These findings provide an understanding of the specific rainfall predictors within the sub-region, providing a basis on which to generate seasonal climate forecast products at a reduced geographical scale.

Utilization of these findings in generating forecasts products has the potential to improve forecast quality (Hansen, 2005), especially in the semi-arid southeast Kenya that is characterised by interannual rainfall variability.
However, these conclusions have to be qualified with some elements of uncertainty. Seasonal climate forecast are probabilistics, and the skill of prediction using SSTs remains low. This is a challenge to climate scientists who should work round the clock to improve the skill of forecast. Although the relationship between OND rainfall in east Africa and the Indian Ocean SSTs is deteriorating (Hastenrath, et al., 2004), future studies should include Indian Ocean SSTs to determine their role in OND rainfall variability in southeast Kenya.

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