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SEASONAL FORECASTING OF THE ETHIOPIAN SUMMER RAINS

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ABSTRACT

We present a new seasonal forecasting model for the June–September rains in Ethiopia. It has previously been found that the total June–September rainfall over the whole country is difficult to predict using statistical methods. A detailed study of all available data shows the rainfall seasonality varies greatly from one region to another, which would explain why the total June–September rainfall over all regions is a difficult property to forecast. In addition, the correlation between rainfall and the southern oscillation index varies spatially, with a strong teleconnection present only in some regions. This study accounts for the spatial variability in rainfall by grouping the rain gauge stations into four geographical clusters based on seasonality and cross-correlation of rainfall anomalies. Linear regression equations are then developed separately for each cluster. The variables we use for the regressions are sea-surface temperature anomalies in the preceding March, April and May of the tropical western Indian Ocean, the tropical eastern Indian Ocean, and Niño3.4. Formal skill testing of the equations shows that the new forecasting scheme is more effective in central western Ethiopia than either climatology or persistence — the methods currently used by the Ethiopian National Meteorological Services Agency. Copyright © 2004 Royal Meteorological Society.

KEY WORDS: Ethiopia; rainfall; seasonal forecasting

1. INTRODUCTION

Africa is particularly vulnerable to the effects of flood and drought, and for this reason a successful seasonal forecasting system would have great economic and social value. The Ethiopian climate has large interannual variability, which is reflected in frequent droughts. For example, the devastating droughts during the 1970s and 1980s resulted in a humanitarian catastrophe. In response, since the 1980s, the National Meteorological Services Agency (NMSA) of Ethiopia has tried various methods of seasonal forecasting. Easy access to numerical weather prediction (NWP) weather products now opens up the possibility of developing statistical methods of seasonal forecasting using lagged correlations of model fields. This paper outlines the development of one such method, a simple linear regression system based on sea-surface temperature (SST) statistical associations.

The methods of forecasting used by the NMSA are based on analogue, trend analysis (short-term trends of SST), statistical assessments, and teleconnections (Bekele, 1993). The first experimental seasonal forecast based on El Niño effects was made in 1987 (Haile, 1987). The basic principle underlying all these methods is the association between strong El Niño–southern oscillation (ENSO) events and regional climate anomalies within Ethiopia. The first person to indicate indirectly the presence of a link between the southern oscillation and rainfall variability in parts of Ethiopia was Sir Gilbert Walker. In his calculations of the southern oscillation, one of the variables he used was the Nile flood level, whose major water source is the Ethiopian

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Highlands (Walker and Bliss, 1932). More recently, Quinn (1992) confirmed this, demonstrating that the variability between high and low flood levels of the River Nile is related to the ENSO cycle. El Niño's role in Ethiopian drought was explored by Nicholls (1993). That study associated the severe drought and famine of 1888–89 in Ethiopia with the 1888 strong El Niño warming. Ininda *et al*. (1987), Tadesse (1994) and Camberlin (1995) have also described the close association between El Niño events and drought over Ethiopia.

A growing body of evidence suggests that Indian Ocean processes also play an important role in controlling African rainfall (e.g. Goddard and Graham, 1999; Latif *et al*., 1999; Black *et al*., 2003). Although all three of these studies focus on equatorial coastal regions, rather than on Ethiopia, studies of the dynamics of the Indian Ocean basin as a whole suggest that Indian Ocean processes affect Ethiopian climate. For example, Cadet and Diehl (1984) identified the warming over the western Indian Ocean in the area of the Somali Current and the southwestern Indian Ocean as important characteristics of the year 1972, a drought year in Ethiopia.

The published literature has focused mainly on the controls on large-scale droughts over the whole of Ethiopia. In this paper, we argue that there are significant inhomogeneities in the rainfall patterns due to orography and local climate conditions. This complexity is also reflected in large deviations in the strength and (in the February–March season) even in the polarity of ENSO teleconnections. Therefore, to progress from a broad understanding of the role of ENSO in controlling average Ethiopian rainfall to an operational seasonal forecasting system, it is essential to account for the modulation of global teleconnections by local physical factors. The first part of this paper describes a method of addressing this problem by dividing the rain gauges into clusters using criteria that include rainfall regime, geographical proximity, and cross-correlations of standardized rainfall.

The main part of the paper is a description of the development of a seasonal forecasting model for the Ethiopian summer rains using SST data for March, April and May in the Indian and Pacific Oceans. Although some seasonal forecasting systems (notably the statistical method used at the Indian Meteorological Department) put many weather variables into their regression systems, in this study the rainfall is predicted using SST only. It is possible that the addition of other climate parameters would improve the skill of the forecasting model. Moreover, experimentation with different variables would certainly be part of the development of an operational system. A simple model is, however, best for the purposes of this study, which aims to address basic problems, such as the implications of spatial variability in rainfall for seasonal forecasting, variation in the predictability of rainfall within the country, and the relationship between the ENSO events and summer rainfall within Ethiopia.

2. THE SEASONAL CYCLE IN ETHIOPIAN RAINFALL

The three rainy seasons which affect Ethiopia are (i) February/March to May, (ii) June/July to September and (iii) October to November. The annual rainfall distribution in the western part of the country has one rainfall maximum during July or August. This 'unimodal' rainfall regime can be subdivided into three sub-regimes, according to the length of the rainy season. In the east of the country the rainfall has a bimodal distribution, with either a long-rain/short-rain pattern (similar to coastal equatorial East Africa) or two seasons of roughly equal length and amplitude. Examples of these rainfall distributions, the locations of the rain gauges, and the cluster boundaries used can be seen in Figures 1 and 2.

This study will focus on the June to September period, which is the main rainy season over a significant portion of Ethiopia. It is estimated that 85 to 95% of the food crop of the country is produced during these months (Degefu, 1987). Thus, deficiency of rainfall is liable to lead to famine over much of the country. During this season, the low-level air circulation over the western half of the Indian Ocean is dominated by the southwest monsoon winds over the Arabian Sea, a strong cross-equatorial flow along the East African coast and over the adjacent ocean, and southeasterly trade winds in the Southern Hemisphere. The high topography of the African coast diverts the main monsoon flow northwards and eastwards. This means that, in Ethiopia, rain during the boreal summer is associated with the migration of the intertropical convergence zone rather than the southwest monsoon winds.

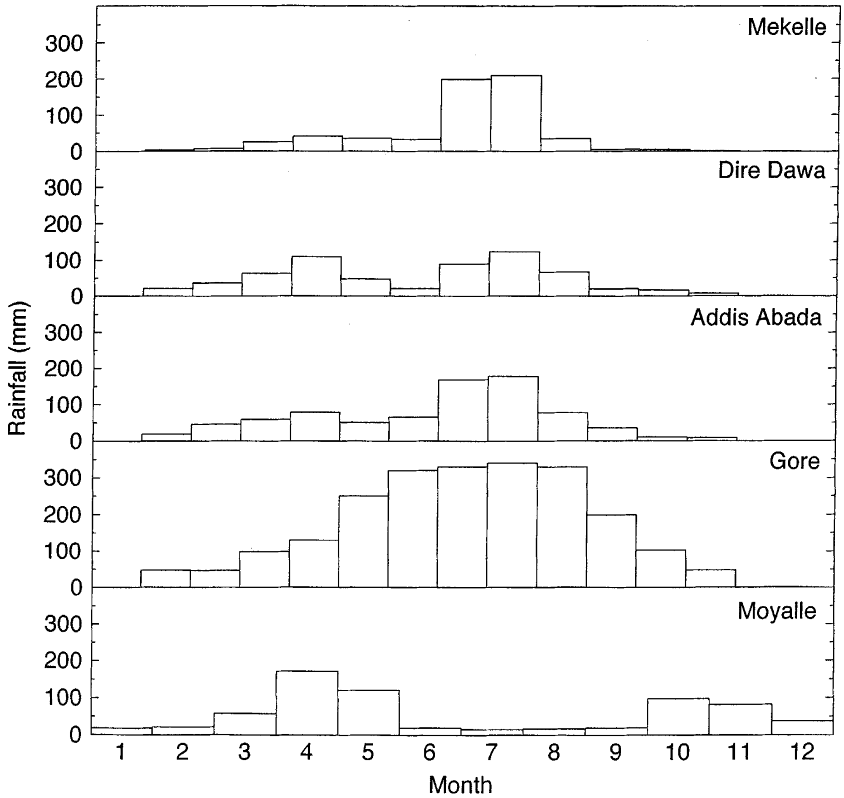

Figure 1. Average annual cycles in rainfall for five of the stations shown in Figure 2

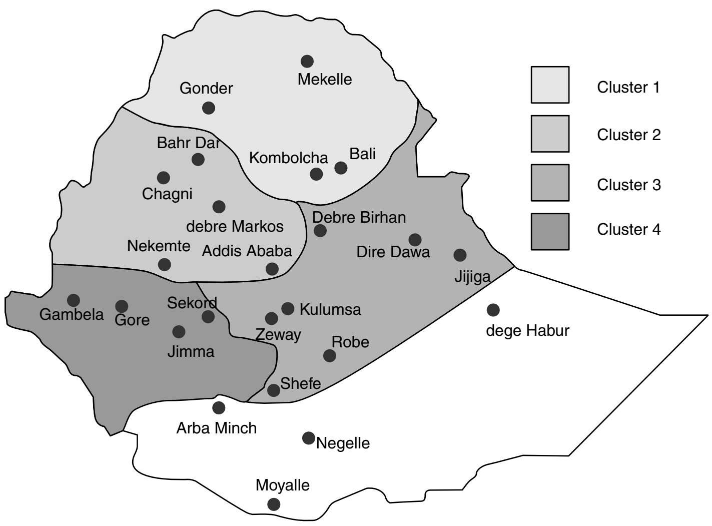

Figure 2. Location of the rainfall clusters and the stations included within them

3. DATA

The variables analysed were rainfall and SST. The available rainfall data consisted of decadal averages (totals) from 42 stations distributed throughout Ethiopia. A dekad is defined as roughly one-third of a month. In each month, the first two dekads correspond to days 1–10 and 11–20, and the final dekad comprises the last part of the month. For this analysis the decadal data were combined into monthly totals. Table I and Figure 2 indicate the locations and time span of the rainfall data. It can be seen that the earliest measurements were made in 1931 and the latest in 1999. The quality of the rain gauge data was variable. Local advice was taken concerning stations that might be unreliable, and, rather than risk contaminating the final results, all such unreliable stations were excluded, leaving a total of 26. There is an inevitable trade off between exclusion of station data and loss of representativeness with respect to the area mean. To confirm that the remaining rain gauge observations gave a realistic picture of the average monthly rainfall, the mean station observations were compared with cold cloud duration (CCD) data derived from Meteosat thermal infrared (TIR) imagery. The CCD is the amount of time for which the pixel temperature (as seen from the TIR image) is colder than a specified threshold. It has been shown that, throughout much of Africa, there is a good correlation between CCD and convective rainfall amount (Grimes *et al*., 1999). The comparison was carried out for the time period 1994 to 1999 for which coincident rain gauge and Meteosat data were available.

The time period over which the data were recorded varied considerably between the stations (see Table I). An analysis period of 1970–97 was used for this study, and stations which did not record data over most of this period were excluded from further analysis. After this process, 19 stations remained. The analysis was

Table I. Data availability for the stations and the cluster they have been allocated to. Stations described as 'south' were not allocated to a cluster because they are in southern Ethiopia, which does not have a summer rainy season. Two stations were excluded: Chagni, because it did not cover the whole analysis period, and Sekoru, because it is in almost the same position as Awassa

Station	Data availability	Cluster
Addis Ababa	1951–97	2
Arba Minch	1970–99	South
Awassa	1972–99	3
Bahr Dar	1961–97	3
Bati	1963–99	1
Chagni	1973–90	Excluded
Debre Birhan	1954–98	2
Debre Markos	1953–97	3
Dege Habur	1954–97	South
Dire-Dawa	1952–99	2
Gambella	1951–93	4
Gode	1970–97	South
Gore	1953–99	4
Gonder	1970–97	1
Jijiga	1952–99	2
Jimma	1952–99	4
Kombolcha	1953–97	1
Kulumsa	1967–99	2
Mekelle	1963–88, 1992–99	1
Moyalle	1931–73, 1979–97	South
Negelle	1953–60, 1964–89	South
Nekemte	1952–97	3
Robe	1962–99	2
Sekoru	1969–97	Excluded
Shefe	1970–97	4
Zeway	1970–99	2

only performed over a 28 year period for two reasons. Firstly, Ethiopian rainfall data are only available in a concentration sufficient for the analysis proposed between 1970 and 1997. Secondly, the simple regression procedure used in this study depends on the assumption that the statistical association between SST and Ethiopian rainfall is stationary. The longer the data period used, the more dubious this assumption because of the possibility of long-term climate change being represented in the data. Thus, 28 years was considered a long enough period to have confidence in the significance of the results (see Section 5.2) while not being so long that decadal variability invalidated the assumption of statistical stationarity.

The rainfall data were used in conjunction with the historical reconstruction of SST by Parker *et al*. (1995), the Global Sea Ice and Sea Surface Temperature (GISST) dataset. The data are presented as monthly means and interpolated over a global grid of resolution 3.75° longitude by 2.5° latitude. The time span of the GISST data is January 1872–August 1998. However, in this study only the data between 1970 and 1997 were used.

4. METHODOLOGY

The aim of this study was to develop a seasonal forecasting model for Ethiopian summer rainfall using a simple regression method. There were several stages to this. The rainfall stations were first divided into clusters based on rainfall seasonality and spatial coherence. Monthly time series of rainfall anomalies were derived for each cluster. These were then used to investigate SST correlations, which highlighted areas of importance within the tropical oceans for predicting the rainfall in Ethiopia. Finally, these predictive associations were used to develop a statistical forecasting model for summer rainfall in Ethiopia.

4.1. Clustering of rainfall stations

Two independent criteria were used to divide the rainfall stations into clusters: the seasonal cycle in rainfall and the coherence of the interannual variability. These criteria, along with the geographical proximity of stations, were used to divide the stations into four groups. The validity of the methodology was tested by comparing the rain gauge observations with CCD data for one of the clusters.

4.1.1. Seasonal cycle in rainfall. The whole of northern and eastern Ethiopia experiences two rainy seasons: February/March to May, and June/July to September (see Section 2). The region is divided by the Great Rift Valley, which marks a transition in the topography from craggy and mountainous in the north to low-relief escarpments and plateaus in central Ethiopia. Although the seasonal cycle in rainfall suggested that the whole of northeastern Ethiopia could form a single cluster, after further analysis the region was subdivided into clusters 1 and 2 (see Section 4.1.2).

The whole of western Ethiopia has a mono-modal rainfall regime. However, there is significant variation in the duration and timing of the rainy season. The north of the area has one fairly intense season between June and September; western central Ethiopia, in contrast, experiences continuous rainfall between February and October. Furthermore, the correlations between rainfall recorded at stations in the north and that observed in the south are weak (see Section 4.1.2). For these reasons, western Ethiopia was divided into two clusters, with cluster 3 in the north and cluster 4 in the central region.

4.1.2. Coherence of the interannual variability. The second criterion used to divide the stations into clusters is the coherence of the interannual variability. To investigate this quantity, the cross-correlation between all the stations for June–August rainfall was calculated. This analysis was used to confirm and further subdivide the clusters that had been derived using the seasonal cycle analysis (see previous section).

Table II shows the mean correlation coefficient for stations both within the cluster in question and with stations in every other proposed cluster. Thus, for example, the cross-correlation between cluster 1 and cluster 2 would be the mean of the cross-correlations between every station in cluster 1 and every station in cluster 2; and the cross-correlation for cluster 1 would be the mean of the cross-correlations between of all the stations in cluster 1. It is evident from Table II that, for all of the clusters except cluster 4, the interannual variability

Table II. Mean cross-correlations between stations within the clusters and with stations in the other clusters

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Cluster 1	0.746	0.274	0.366	0.156
Cluster 2	0.274	0.647	0.484	0.132
Cluster 3	0.366	0.484	0.965	0.180
Cluster 4	0.156	0.132	0.180	0.240

of rainfall within a given cluster is reasonably coherent. Moreover, the correlations between rainfall stations within clusters are stronger than the correlations between stations in different clusters, thus justifying the decision to divide the region in this way.

4.1.3. Validating the methodology using CCD data. This study is concerned in principle with the areal mean rainfall over each cluster area as defined in Figure 2. An important question is how reliable the rain gauge data are as a representation of area mean rainfall. This was qualitatively assessed by comparison with CCD data from Meteosat. The comparison is shown in Figure 3. As the resolution of the CCD pixels is small, we expect reasonable correspondence between rain gauge totals and CCD totals for the pixels containing the gauges. The upper panel of Figure 3 demonstrates that this is the case, with the correlation between rain gauges and CCD data being 0.91. This indicates that the CCD rainfall estimate is a good proxy for actual rainfall in Ethiopia. The lower panel of Figure 3 shows the spatial average for all CCD pixels in each cluster area versus the CCD rainfall estimate using the pixels containing the rain gauges. The high correlation between the CCD area-average rainfall and the estimate from the rain gauges is at least a qualitative indication that the rain gauge time series represents the spatial average rainfall over the whole cluster area.

4.2. Development of a linear regression model

4.2.1. Choice of input variables: teleconnections and lead times. For a regression model to have skill, there must be a reasonably strong linear correlation between the variable being predicted (in this case June–September (JJAS) rainfall) and some other variable (in this case SST). Therefore, the first stage of model development was analysis of the statistical association between the JJAS standardized rainfall anomaly and global SST. The SST regions that were strongly associated with Ethiopian rainfall were then used as inputs into the regression process. For a forecast, it is obviously necessary to use SSTs in advance of the season in question, and in this case a sensitivity study was used to define a feasible lead time for the forecast model.

The global statistical associations between SST and Ethiopian rainfall were assessed by calculating the linear correlation between JJAS rainfall and JJAS SST at all grid points (see Figure 4). The data period used was 28 years. For this number of years, the correlation required for significance at the 95% level (two-tailed) is ± 0.37. It is evident from Figure 4 that, for clusters 2 and 3, the correlations within both the Pacific and Indian Oceans are statistically significant. Cluster 3 in particular has a strong association with both the eastern and western Indian Ocean in the regions highlighted by Saji *et al*. (1999) as forming the poles of the Indian Ocean dipole (IOD) or zonal mode. For clusters 1 and 4, the correlations are generally weaker and the correlations in the Indian Ocean are significant over a smaller area.

In order to determine which regions and time leads should be put into the final forecasting model, two sensitivity tests were carried out. These involved carrying out a multiple-linear regression between the rainfall observed in cluster 3 and the various combinations of variables. The correlation between the regressed (predicted) rainfall and the observed rainfall was then calculated. Clearly, changing the quantity of variables in the prediction scheme alters the number of degrees of freedom. Therefore, in order to make the results comparable the significance of each calculated correlation was derived. The significance was calculated using a two-tailed t-test. Rainfall in cluster 3 was used for the sensitivity tests because cluster 3 exhibited the strongest associations with remote SST and, hence, was considered the most promising cluster in terms of seasonal predictability.

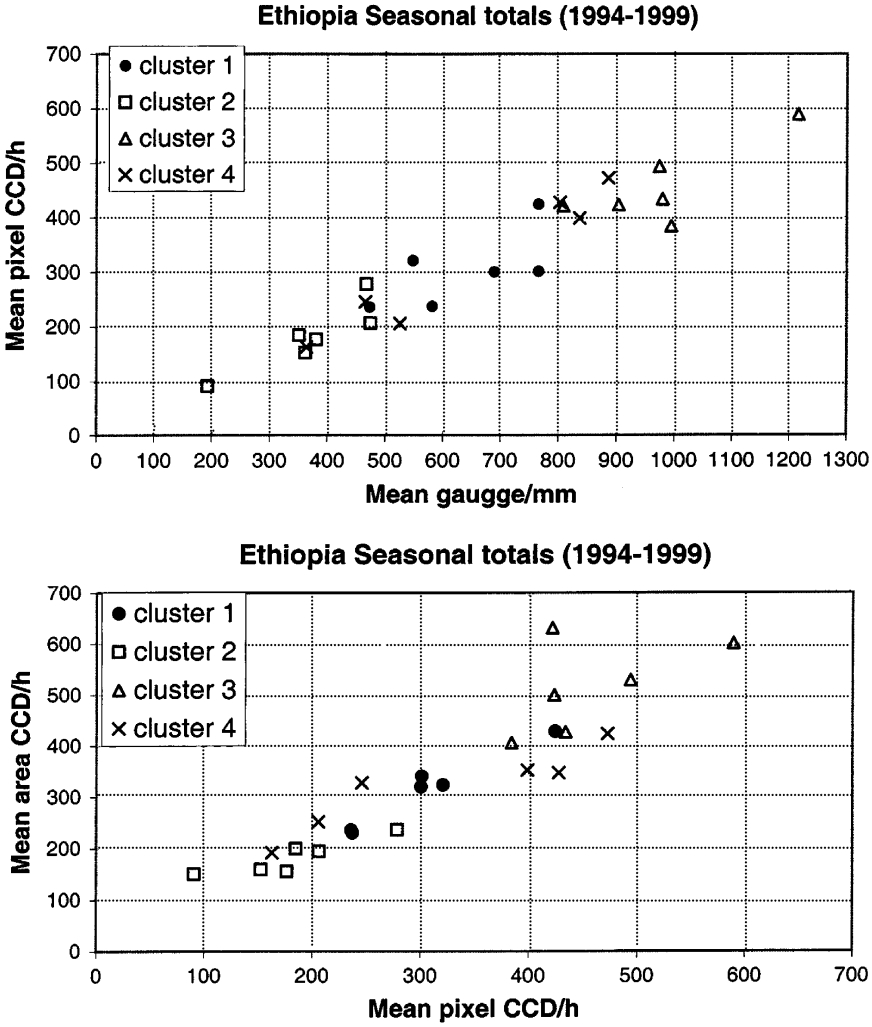

Figure 3. CCD estimates of rainfall within the clusters compared with gauge measurements. Individual points are rainfall estimates for each year in which there was overlap between the gauges and the satellite rainfall estimates. The upper figure shows mean rain gauge measurements versus the CCD rainfall estimate for the pixel containing the gauge. The lower figure shows the single-pixel CCD rainfall estimate versus the area-averaged rainfall for all the pixels within each cluster

The main regions associated with Ethiopian rainfall are the western Indian Ocean, the eastern Indian Ocean and the eastern Pacific Ocean. Although these regions are known to be correlated strongly with each other, recent work has suggested that Indian Ocean SST affects the climate of the surrounding continents independently of ENSO (see Black *et al.* (2003) and Saji *et al.* (1999)). Therefore, a sensitivity test was performed to determine whether incorporating the Indian Ocean into a prediction model would be likely to add skill to the forecasts. A multiple-linear regression analysis was carried out using March, April and May SST to predict JJAS rainfall in the cluster. First, only the Niño3.4 region was used. This was then compared against an analysis using all three regions. It was found that, when all three regions were included, the correlation coefficient between observed and predicted rainfall was 0.6 (significance level of approximately 99%). In contrast, when the Niño3.4 region was used by itself, the correlation coefficient fell to 0.3 (significance level of approximately 90%). Therefore, all three regions were included in the analysis.

The question of whether to include March, April and May SST or just to use May alone was tackled in an analogous manner. It was found that, when only May SST was included in a multiple-linear regression

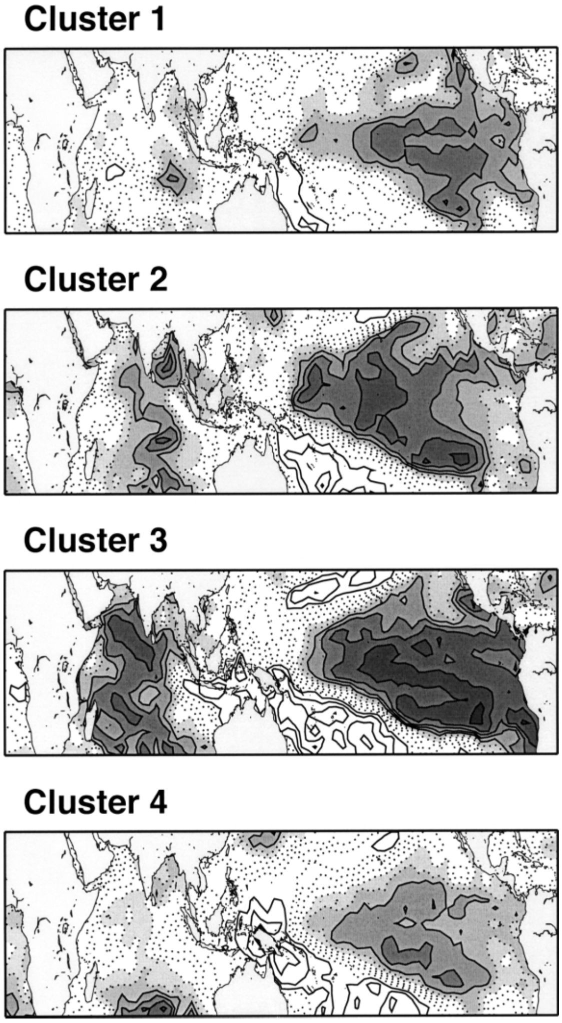

Figure 4. Linear correlation between SST and rainfall during the JJAS rainy season in each of the clusters shown in Figure 3. Negative values are shaded; correlations that are significant at the 95% level are contoured with solid lines and insignificant correlations are contoured with dotted lines. The contour interval is 0.1

model, the correlation between observed and predicted rainfall fell from 0.6 (when all 3 months were used) to 0.4 (significance level of approximately 95%). For this reason, it was decided to use March, April and May SST for all three regions.

In summary, therefore the SST regions put into the regression model were:

1. The tropical western Indian Ocean (10 °S–10 °N, 50–70 °E).
2. The tropical western Indian Ocean (10 °S–equator, 90–110 °E).
3. The Niño3.4 region of the tropical Pacific (5 °S–5 °N, 120–170 °W).

4.2.2. The regression process. The equation of the linear regression forecast model was formulated as follows:

$$Y = a1x1 + a2x2 + a3x3 + a4x4 + a5x5 + a6x6 + a7x7 + a8x8 + a9x9 \quad (1)$$

where $a1$–$a9$ are coefficients determined from the regression process and the input variables, $x1$–$x9$, are SST during March, April and May of the tropical west Indian Ocean, the tropical southeast Indian Ocean, and the Niño3.4 region of the Pacific.

Values for parameters $a1$–$a9$ are obtained by a least-squares fitting procedure using the observed data. It is also necessary to retain some data to validate the optimized equation. One approach is to split the data into two subsets (e.g. Farmer (1988) for Kenyan rainfall). This approach was not adopted here. Instead, a cross-validation method was employed in which for a time series of n years, $n - 1$ years are used for calibration and the remaining year is used to validate the model. This process is then repeated n times, with a different year as the validation target in each case. This approach is preferred for three reasons. First, it makes most efficient use of the relatively short dataset (in our case allowing 27 years of data in each calibration). Second, it is more robust in the presence of long-term climate variability, which should show up as a gradual drift in the regression parameters. (3) Third, it is closest in principle to an operational model in which all available past data would be employed to calibrate the model to predict the current season.

It can be seen that there were nine predictors of rainfall. The cross-validation method employed in this study used 27 years of data to predict every year. Having nine predictors in the regression model is, therefore, not a case of overfitting the data. Moreover, in the analysis there was no evidence of numerical instability. In particular, excluding a single point from the data as part of the cross-validation process did not cause large changes in the predicted values for the other years.

5. RESULTS

5.1. Observed and forecast rainfall: general observations of the forecast quality

The observed and forecast rainfall time series are shown in Figure 5. It can be seen that in all four clusters there were examples of very successful forecasts and serious failures. In cluster 1, there were highly

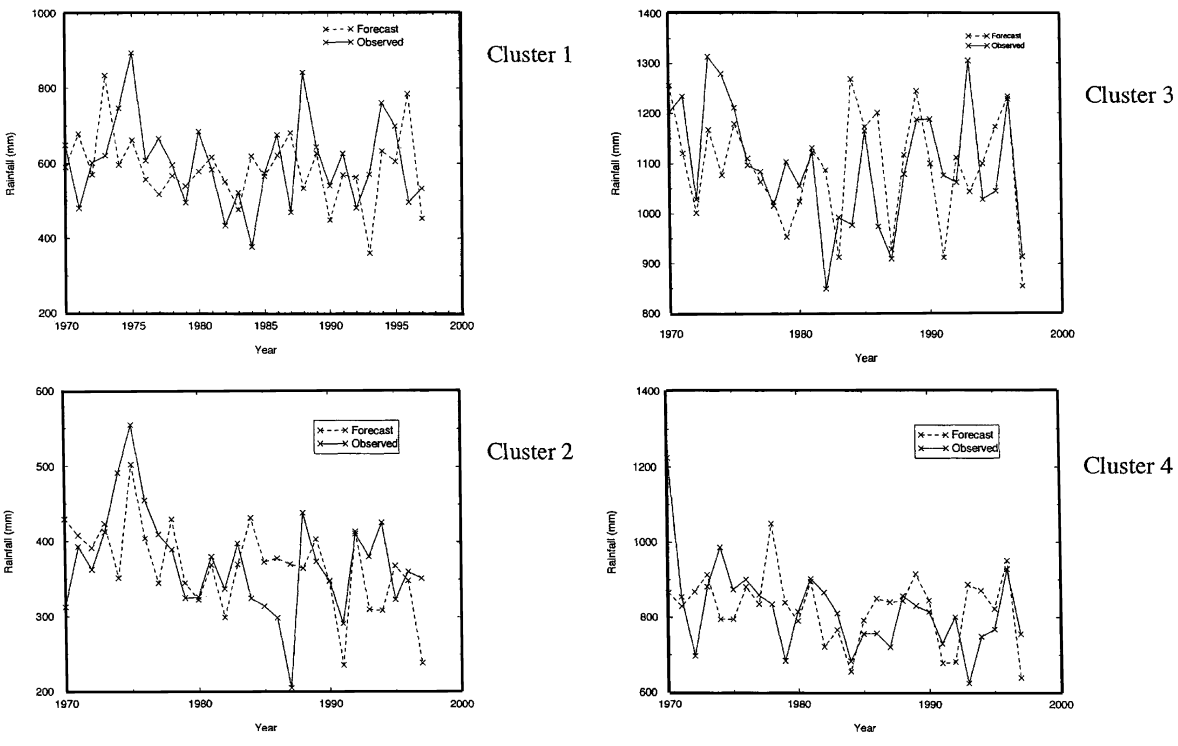

Figure 5. Observed and forecast rainfall for all four clusters using the regression method

successful forecasts during years when the El Niño forcing was very strong (1972, 1982 and 1997), a result that is consistent with the relatively strong SST correlations in the eastern Pacific shown in Figure 4. The fact that there were several years of very low and high rain which were not associated with El Niño or La Niña suggests that some of the climate variability is related to factors other than ENSO or Indian Ocean dynamics, a hypothesis borne out by the comparatively weak correlations with global SST (see Figure 4).

For cluster 2 there appears to be some interdecadal variability in the success of the forecasts, with the forecasts being quite successful in the 1970s, remarkably successful in the 1980s and early 1990s, and completely wrong in the mid-1980s and mid and late 1990s. The regression seems particularly good at predicting drought (two out of the three worst droughts successfully predicted) but less good at predicting high rainfall, which is perhaps a reflection of the nonlinearity of El Niño/La Niña teleconnections.

Cluster 3 gives the best match between observed and predicted seasonal totals. The forecast succeeds very well in several years, notably the 1997 and 1972 droughts. The general magnitude and pattern of interannual variability is also captured. However, there were failures, e.g. 1982, 1986 and 1991–94. A similar pattern of failure was seen for cluster 2, and this suggests that the method may sometimes fail because of anomalous seasonality of El Niño. For example, the regression did badly in 1986–87, during which an El Niño with unusual seasonality developed. Similarly, the failure of the model in the early 1990s coincides with an extended and anomalous El Niño between 1991 and 1994.

The rainfall in cluster 4 does not seem to be as strongly related to the El Niño cycle as the other clusters, an observation that is consistent with the correlations illustrated by Figure 4. There were, however, some successful forecasts. For example, the drought in 1984 was correctly predicted. The correlations were very weak for cluster 4, and so the general lack of success might have been expected.

5.2. *Formal assessment of forecast skill*

5.2.1. Methodology used to assess forecast skill. For most practical operational purposes, it is not necessary to know exactly how much rain might be measured in a given rain gauge. Therefore, the skill of the forecast has been measured in semi-quantitative terms as follows: the observed rainfall distribution was divided into deciles and the forecast rainfall distribution was also divided into deciles (distinct from the observed deciles to allow for systematic error in the forecast rainfall distribution). The observed and forecast rainfall deciles were then compared and subjected to a hierarchy of tests.

The significance of the results was estimated using contingency table theory. A version of Fisher's exact test of significance was adapted for the investigation of ENSO teleconnections in Mason and Goddard (2001). An analogous method is used here. In this test, the significance of the number of times that the forecast model successfully forecasts the rainfall is equivalent to the probability of picking at least this number at random. This probability can be expressed as

$$p(X \geq x) = H(x; r, b, n) = \sum_{k=x}^{\min(r,b)} \frac{\binom{b}{k}\binom{n-b}{r-k}}{\binom{n}{r}} \tag{2}$$

$p(X \geq x)$ is the probability that the number of hits X is greater than or equal to some value x; b is the number of years that are observed to have the characteristic we wish to forecast; r is the number of years forecast to have the characteristic we wish to forecast; n is the total number of years. The meaning of these parameters is further clarified in Table III. The way that Equation (2) was approximated is given in the appendix to Mason and Goddard (2001).

5.2.2. The skill of the forecasts. The regression forecasts were subjected to a hierarchy of tests, starting with completely qualitative and ending with a semi-quantitative forecast. The first test of the forecast was its ability to make very broad hit/miss forecasts. The current form of forecasts issued in Ethiopia is either 'below average–average' or 'average–above average'. Deciles 1–5 were defined as below average–average

Table III. Structure of contingency table for forecasting some event, defining the variables in Equation (2)

Observed	Forecast		
	Yes	No	Total
Yes	x (number of hits)	$b - x$ (number of misses)	b (total number years where an event was observed)
No	$r - x$ (number of false alarms)	$n - r - b + x$ (number of years with no event, where no event was forecast)	$n - b$ (total number years where no event was observed)
Total	r (total number of years where an event was forecast)	$n - r$ (total number of years where no event was forecast)	n (total number of years)

and deciles 6–10 as average–above average. The contingency table method described in Section 5.2.1 was applied to the results. In our case, for the forecasts of above average to below average, the total number of years $n = 28$. The skill was assessed separately for the average–above average and average–below average years. The results are shown in Table IV. It can be seen that the clusters have widely differing skills. According to this analysis, they may be ranked as follows: cluster 3, cluster 1, cluster 2 and cluster 4; cluster 3 having good skill and clusters 4 and 2 being little better than chance.

The next test of the model was to see how well it predicted rainfall terciles (average, below average and above average). The significance of the results was calculated separately for each of the terciles within each of the clusters. The results are shown in Table V. Again, cluster 3 shows by far the best skill.

Finally, the regression forecasts were compared with those that would be obtained if the rainfall were predicted to be the seasonal average (climatology) or the same as the previous year (persistence). Figure 6 shows a cumulative histogram of decile difference between observed and forecast rainfall for each of these methods. It can be seen that, for cluster 3, 50% of the regression forecasts were within one decile of the observed. This compares with 35% when climatology is assumed and 33% when persistence is assumed — a clear improvement. For the other clusters, it is clear that the regression forecast is no better than climatology or persistence. In particular, for cluster 4, the model is worse than persistence and only as good as climatology in making successful predictions within ± 1 decile.

Table IV. Percentage of correct forecasts for 'average–below average' and 'average–above average' resolution using the regression method

	Number			
	Forecast	Observed	Hits	Significance (%)
Cluster 1				
Dry	14	14	9	87
Wet	14	14	9	87
Cluster 2				
Dry	14	15	9	78
Wet	14	13	8	78
Cluster 3				
Dry	14	13	9	94
Wet	14	15	10	94
Cluster 4				
Dry	14	14	8	65
Wet	14	14	8	65

Table V. Percentage of correct forecasts for 'below average', 'average' and 'above average' resolution using the regression method

	Number			
	Forecast	Observed	Hits	Significance (%)
Cluster 1				
Dry	9	10	4	60
Average	10	9	4	60
Wet	9	9	3	38
Cluster 2				
Dry	10	9	3	28
Average	9	10	2	7
Wet	9	9	4	70
Cluster 3				
Dry	9	9	5	94
Average	10	10	6	95
Wet	9	9	5	94
Cluster 4				
Dry	9	10	4	60
Average	10	9	4	60
Wet	9	9	4	70

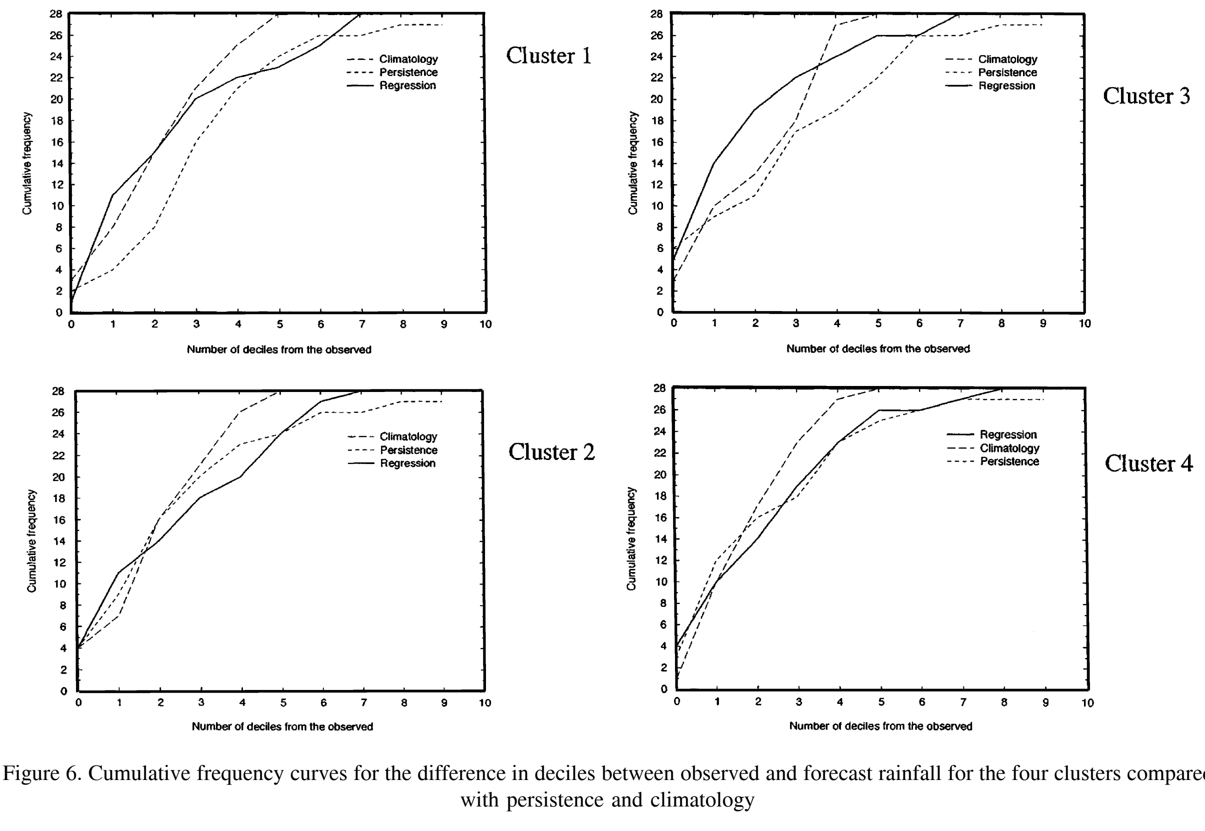

Figure 6. Cumulative frequency curves for the difference in deciles between observed and forecast rainfall for the four clusters compared with persistence and climatology

6. OPERATIONAL FEASIBILITY

At present, the Ethiopian Meteorological Service uses a combination of methods to produce a forecast whether Ethiopia will have a 'below average–average' or 'average–above average' rainy season. These methods include persistence, climatology (to determine regional, spatial variation) and SST indicators of an impending El Niño. The proposed method has several advantages over the present methods used. First, it identifies areas within which forecasts are likely to be useful. Second, it has greater skill in the cluster 3 region. Third, it provides a semi-quantitative forecast. For the forecast to become useful at an operational level, further development of the model will be necessary to improve skill and to determine the error bounds of the forecast. Detailed analysis of individual years in which the forecast failed may identify characteristics of the SST field that make the forecasting system unreliable. The present regression model only has skill if May SST data are included. As coupled models continue to improve, it may be possible to issue forecasts earlier based on predicted SST.

The model is easy to adapt and change without recourse to advanced computing. The analysis would have been possible using the computing facilities presently available at the NMSA. The forecast, however, does depend on the availability, in real time, of high-quality meteorological data and analyses. The continued provision of such data is, therefore, essential for countries like Ethiopia to develop and operate their own seasonal forecasting models.

7. CONCLUSIONS

1. Ethiopian rainfall is highly variable, both temporally and spatially, and so must be analysed in clusters rather than as a whole.
2. Four clusters of rainfall stations can be identified using cross-correlations and analysis of rainfall seasonality.
3. Satellite imagery has been used to confirm that available gauges are representative of the cluster areas. This analysis also confirmed that CCD is a good proxy for rainfall in Ethiopia.
4. The statistical association between rainfall in the four clusters and remote SST varies greatly in strength, with the west of the country (cluster 3) having the strongest associations with Indian and Pacific SST.
5. A linear regression method incorporating Indian and Pacific SSTs in the March, April and May leading to the JJAS rainy season can be used to develop a skilful forecast for part of Ethiopia (cluster 3).
6. With further model development, and providing adequate data are freely available, the linear regression method may provide the basis of an operational seasonal forecasting system for Ethiopia.

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