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**Original citation & hyperlink:**
Eden, JM, Widmann, M & Evans, GR 2014, 'Pacific SST influence on spring precipitation in Addis Ababa, Ethiopia' *International Journal of Climatology*, vol 34, no. 4, pp. 1223-1235
https://dx.doi.org/10.1002/joc.3759

DOI 10.1002/joc.3759
ISSN 0899-8418
ESSN 1097-0088

Publisher: Wiley

# Pacific SST influence on spring precipitation in Addis Ababa, Ethiopia

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**ABSTRACT:** Recent periods of drought in Ethiopia and other parts of East Africa have highlighted the growing importance of producing reliable forecasts of seasonal precipitation. Key in deriving such forecasts is a good understanding of the atmospheric and oceanic drivers of different precipitation regimes. In Ethiopia and other parts of East Africa, interannual variability of precipitation depends on variations in sea surface temperature (SST) and atmospheric circulation on both regional and global scales. Links between summer precipitation in Ethiopia and large-scale modes of climate variability such as ENSO have previously been established but the influence of global SST on spring precipitation has not yet been fully explored. Here, we analyse the links between Pacific SST and precipitation in Addis Ababa, Ethiopia for a century-long period (1900-2004). A tripole correlation pattern between spring precipitation and SST in the Pacific basin is found. We develop regression-based models to estimate spring precipitation from Pacific SST with a lead time of 2-3 months. When subject to cross-validation, models based on principal component multiple linear regression (PC-MLR) calibrated on Pacific SST during December show substantial skill in reproducing observed temporal variability in Addis Ababa precipitation during February (r = 0.48) and March (r = 0.40), and the period spanning February to April (r = 0.44). Our findings suggest that the inclusion of Pacific SST in predictive models may benefit drought forecasting across Ethiopia.

**Key Words:**

Ethiopia precipitation, seasonal predictability, statistical model, sea surface temperature

## 1. Introduction

Forecasting seasonal precipitation is crucial in regions in which economic and social stability is particularly sensitive to changes in precipitation. Ethiopia is one such region where interannual variability in seasonal precipitation is associated with substantial risk from drought and the subsequent impacts on rain-fed agriculture. The well-publicised drought of 2011 affected large parts of eastern Africa, leading to crop failure and severe food shortages throughout much of Ethiopia, Somalia and Kenya. Understanding the atmospheric and oceanic processes that control interannual precipitation variability, including extreme events such as the 2011 drought, is crucial for developing skilful forecasting methods.

Ethiopia precipitation is characterised by three distinct seasonal regimes: February/March to May (known as Belg), June to September (Kiremt) and the dry season falling between October and January (Bega) (Gissila *et al*., 2004; Seleshi et al., 2004). The Kiremt rains, occurring between June and September, account for 50-80% of annual totals (Korecha and Barnston, 2007) and are most prominent in the north and west of the country. Typically, it is low precipitation during the summer months that is associated with the most severe droughts throughout Ethiopia (Korecha and Barnston, 2007), and the majority of research into the link between large-scale atmospheric-oceanic controls and the establishment of predictability has focused on the Kiremt rains (e.g. Segele and Lamb 2005; Korecha and Barnston, 2007; Block and Rajagopalan, 2007). By contrast, relatively little work has been done on the potential for predictability of precipitation during the Belg, which is of great importance to much of southern Ethiopia and, to a lesser extent, the Ethiopian highlands as part of a bimodal annual precipitation regime (Seleshi and Zanke, 2004; Diro *et al*., 2008). Failure of the Belg rains may have important agricultural implications, particularly for long-cycle crops, such as maize and sorghum, which require the full extent of the spring-summer growing season (Verdin *et al*., 2005; Cheung *et al*., 2008).

The potential for exploiting any predictability that might exist is greatest when the local mechanisms involved in precipitation formation are well-understood. Precipitation during the Kiremt is largely dominated by the northward advance of the Inter-Tropical Convergence Zone (ITCZ), the position of which has important implications for precipitation onset, duration and cessation in different parts of (particularly northern) Ethiopia. A number of additional factors influence Kiremt precipitation, including the development of thermal lows over the eastern Sahara and Arabian Peninsula, the position of the upper-tropospheric Tropical Easterly Jet (TEJ) over Ethiopia (Seleshi and Zanke, 2004; Baker *et al*., 2007; Korecha and Barnston, 2007), and the development of the low-level Somali Jet during late spring (April-May), which is known to enhance mean close-to-surface south-westerly flow when the jet achieves greater stability during the summer months (Seleshi and Zanke, 2004; Riddle and Cook, 2008).

These regional controls are likely to be influenced by large-scale atmospheric or sea surface temperature (SST) anomalies, and the link of such anomalies with the Kiremt precipitation has been previously investigated. For example, Segele and Lamb (2005) compared atmospheric temperature, SST, geopotential height and pressure fields during selected dry and wet Kiremt seasons and found a discernible influence of equatorial Pacific SST on Kiremt precipitation, with warm SST anomalies associated with an early Kiremt onset and a shorter growing season. Several attempts have been made in linking Kiremt precipitation variability to variations in the El Nino Southern Oscillation (ENSO) (e.g. Seleshi and Demaree, 1995; Segele and Lamb, 2005), which is known to be associated with variability in the ITCZ (Nicholson, 2000). In general, anomalously high (low) Kiremt precipitation has been shown to coincide with cold (warm) phases of ENSO (Segele *et al*., 2009). Linkages between Kiremt precipitation and ENSO states, or otherwise Pacific SST anomalies, have also formed the basis of predictability studies (e.g. Gissila *et al*., 2004; Block and Rajagopalan, 2007). Korecha and Barnston (2007) showed ENSO to be the primary influence on Kiremt precipitation and that ENSO-based forecasts with a lead time of two months can be used to predict summer precipitation with some skill.

The mechanisms controlling precipitation are markedly different during the Belg season and not yet fully understood (Camberlin and Philippon, 2002; Diro *et al*., 2008). The dominant atmospheric feature during the Belg is the movement of the Arabian high toward the north Arabian Sea, which coincides with the formation of a thermal low over southern Sudan and leads to moist easterly and south-easterly winds, which are drawn towards this thermal low from highs in the Gulf of Aden and the Indian Ocean respectively. This moisture transport is responsible for the heavy spring precipitation in southern Ethiopia and the 'small' rains across the Ethiopian highlands. The presence of tropical depressions in the south-west Indian Ocean is known to be associated with reduced precipitation in Ethiopia, particularly during the Belg, which corresponds with the period of most intense cyclonic activity in this region (Shanko and Camberlin, 1998; Seleshi and Zanke, 2004). The extent to which these features are in turn associated with large-scale SST anomalies or the phase of ENSO is uncertain (Camberlin and Philippon, 2002).

It is the purpose of this paper to investigate the link between global SST and Belg precipitation and to examine the potential for statistical Belg predictions using SST as a predictor. In addition to its distinct climatological rainy seasons, Ethiopia's topographical diversity presents another challenge for formulating statistical prediction models. Much previous work has taken precipitation data from multiple locations throughout Ethiopia (e.g. Gissila *et al*. 2004; Diro *et al*., 2008), which acknowledges the regionally-varying contributions of different climatic regimes to precipitation. However, the majority of precipitation records are often incomplete or lacking in quality. Additionally, the multitude of short records does neither permit a robust analysis of statistical links on interannual timescales nor any investigation of links on decadal timescales. Here, comparisons with global SST are made using the longest and most complete record, which is a solitary century-long precipitation record for Ethiopia's capital city Addis Ababa (Conway *et al*., 2004). Addis Ababa lies in the geographical centre of the country and is influenced by both the Belg and Kiremt precipitation regimes.

For investigating the potential for predictability, it is useful to ask two questions:

- What teleconnections exist between global SST and Addis Ababa precipitation (hereafter AAP)?
- To what extent does the partial predictability of SST over a few months lead to predictability of AAP from SST?

Many previous examples of statistical predictive models based on SST anomalies have used area-averaged SST means or indices describing large-scale modes of variability such as ENSO. In contrast, we have taken a bespoke approach that uses SST predictor patterns that are based on the statistical relationships between SST and AAP. These patterns are used in the formulation of regression-based models, which are then subjected to a rigorous cross-validation in order to assess their skill in representing temporal variability in spring AAP.

## 2. Data and methods

### 2.1 Addis Ababa precipitation, SST and atmospheric data

Ethiopia is located within 3° to 15°N and 33° to 48°E and is dominated by a high, central plateau, which is bisected in a southwest-northeast direction by the Great Rift Valley. The Ethiopian highland region lies between the Upper Nile and Ethiopia's border with Eritrea and consists of plateaux that rise towards mountain ranges. The Ethiopia Lowlands are located primarily in the south and east, and exhibit a dry and hot climate. Figure 1 shows the location of Addis Ababa along with Ethiopian topography and details monthly mean precipitation totals.

Monthly precipitation data for Addis Ababa is taken from a century-long (1900-2004) observational record described in Conway *et al*. (2004). Global monthly SST data are taken from HadISST (Rayner *et al*., 2003), which combines monthly globally complete SST fields and sea ice concentration from 1870 to date at a spatial resolution of 1° x 1°. We use HadISST due to its length and its application in previous studies that have focused on Pacific SST links with East Africa precipitation (e.g. Diro *et al*., 2008). Additionally, it has been shown that the interannual and decadal variations in HadISST agree strongly with those of the lower resolution HadSST2 analysis and the night-time marine air temperatures (NMAT) from the Meteorological Office Historical Marine Air Temperature version 4 (MOHMAT4) (Deser *et al*., 2010). However, there are also some important sources of uncertainty to consider. In the development of HadISST, a bias adjustment (Folland and Parker, 1995) was applied to all pre-1942 data. While this adjustment has been supported in additional work (e.g. Folland *et al*., 2001; Smith and Reynolds, 2002), there exist on-going difficulties in linking historical *in situ* observations to modern data leading to subsequent uncertainties (Rayner *et al*., 2003). More specifically, the reliability of HadISST trends in the eastern equatorial Pacific has recently been called into question (Deser *et al*., 2010). The regression models used here are based on detrended data and interannual variability, so potential inhomogeneities and spurious long-term trends do not influence the formulation of each model. It is important to note that the final reconstruction will be influenced by spurious SST trends to the extent that such trends will have a non-zero projection on the weight patterns used in the regression model.

Additionally, atmospheric variables are taken from the ERA-40 reanalysis (Uppala *et al*., 2005), which covers the period between September 1957 and August 2002.

## 2.2 One-dimensional MCA and PC-MLR

When seeking to estimate local meteorological variables from SST or atmospheric fields one may focus simply on area averages of the predictors over regions that may have a link to the predictand. However, when dealing with large spatial domains, it is useful to employ more sophisticated techniques to reduce the dimensionality of the predictors by either using the leading principal components (PCs) or patterns that optimally describe the link to the predictand. A common linear estimation approach for one-dimensional predictands such as the AAP record is to use the leading PCs of the predictor field in a multiple linear regression (MLR) model. This is equivalent to one-dimensional canonical correlation analysis (CCA) (Glahn, 1968; Bretherton *et al*., 1992; Cherry, 1996; Widmann, 2005; Tippett *et al*., 2008). An alternative to PC-MLR is to construct a linear regression model based on maximum covariance analysis (MCA). Widmann (2005) has clarified the relationship between the MCA, CCA and linear regression in the special case of one-dimensional predictands, and the general case of linearly estimating one field from another has been comprehensively discussed by Tippett *et al*. (2008). As shown by Widmann (2005) MCA with a one-dimensional predictand is equivalent to using the time expansion coefficient (TEC) of the regression map of the predictor field onto the predictand as the predictor in a standard, one-dimensional regression; in other words the TEC of the regression map is the linear combination of the original variable anomalies that maximises the covariance with the predictand time series. TECs are in the case of regression maps, or MCA, simply the orthogonal projection of time-dependent anomalies onto the corresponding patterns, whereas for CCA adjoint patterns have to be used (Bretherton *et al*., 1992). TECs of regression maps have been frequently used in climatological studies, for instance by Wallace *et al*. (1995) or Thompson and Wallace (1998), but in these studies the TECs have only been compared to the time series on which the regression maps were defined rather than being used as predictors in a linear regression.

Although PC-MLR maximises the explained variance for the fitting data set by construction while one-dimensional MCA does not, it is not clear which method performs better on independent data (Widmann, 2005; Tippett *et al*., 2008). Here, both PC-MLR and MCA models are developed to estimate spring AAP from SST fields. For both methods an area from which the SST is taken to define the predictors needs to be specified. This is done by first calculating global correlation maps of SST and AAP and then selecting rectangular areas that include the areas of the highest correlations; details will be given in section 3. The SST in these predictand areas is used to either calculate the PCs for PC-MLR or the TEC of the regression map for one-dimensional MCA.

Statistical models constructed using each method are cross-validated using a leave-*n*-out technique (e.g. Wilks, 2006; Eden *et al*., 2012). As with all cross-validation techniques, values of the predictand for a validation period are independently estimated using data from a fitting, or training, period. In a leave-*n*-out approach where $n$=1, precipitation quantities for each year are estimated using an individual prediction model constructed using SST and precipitation data from all other years within the time series, the fitting period thus shifts accordingly for each year validation period. Here, a variation is used where $n$=7; the seven year period centred on the year to be estimated is omitted from the fitting period so as to reduce the possibility of autocorrelation in neighbouring years influencing the analysis. In each case, the precipitation and SST time series are detrended before application in model fitting.

## 3. Controls on Addis Ababa spring precipitation

### 3.1 Local- and regional-scale features

As discussed in section 1, the prevailing synoptic patterns over East Africa differ during the Belg and Kiremt precipitation seasons. Whereas Kirmet rains, which are most intense in the north and west of Ethiopia, are largely determined by the northward movement of the ITCZ and associated westerly air masses, the mechanisms governing precipitation during the Belg tend to develop over the Indian Ocean. Figure 2 details the average sea-level pressure (SLP) and 1000-hPa wind fields in ERA-40 during each month throughout spring. While precipitation during the Belg generally lasts for the whole season, the mean synoptic conditions surrounding Ethiopia exhibit substantial intra-season variability during spring (Figure 2a-d). The biggest change occurs during May when air from the southern Indian Ocean is drawn toward the Horn of Africa and contributes to the early development of the Somali Jet. Thus, wind flow off the Somali coast is in general a reverse of north-easterly movement of air prevalent during February and March, and to a lesser extent April.

It is useful to understand how deviations from the mean synoptic conditions influence precipitation characteristics. Figure 3 details mean wind and SLP anomalies during the five wettest and five driest months in Addis Ababa between 1958 and 2001. It is noted in particular that early development of the Somali Jet is associated with drier conditions during May in Addis Ababa, and that May precipitation is heaviest when the synoptic situation resembles those between February and April. In a study of the dynamics and predictability of spring precipitation over the whole of East Africa, Camberlin and Philippon (2002) call for a separation between March-April and May when attempting to establish teleconnections. It is clearly difficult to make a robust distinction between Belg and Kiremt rains in many parts of Ethiopia. For Addis Ababa, the suggestion made by Camberlin and Philippon (2002) is consistent with our analysis as May, although typically considered part of the Belg season, is characterised on average by lower precipitation totals than in April (Figure 1) suggesting that it may be better classified as a month of seasonal transition.

## 3.2 Relationship with Pacific SST

As regional atmospheric circulation anomalies might be partly forced by SST anomalies, we now investigate to what extent AAP is linked to global SST. Previous studies have noted the relevance of the Pacific Ocean to Ethiopian spring precipitation (e.g. Diro *et al*., 2008) but there remains much to be understood about the mechanisms behind this teleconnection. In this section, we present correlation maps to identify concurrent relationships between AAP and global SST during the spring (FMAM) precipitation seasons, and also during the individual component months of each season (Figure 4).

During spring, the highest AAP-SST correlations (up to ±0.5) are found across the northern and central Pacific basin (Figure 4a). The correlation pattern during February, March and, to a lesser extent, April, can be described as a tripole over much of the central Pacific Ocean with positive correlation in the region of the eastern central Pacific, and the regions of the central Pacific north and south of 15°N and 15°S respectively associated with negative correlation. The regions of strongest correlation appear north of the equator, with a distinctive north-west to south-east gradient across the central Pacific. The magnitude of the AAP-SST correlation are similar to that between Pacific SST and East African precipitation found in previous work (e.g. Diro *et al*., 2008; Segele *et al*., 2009) and suggests scope for predictability.

The relevance of SST for ITCZ movement is pointed out in Chiang *et al*. (2002), where displacement of the Atlantic ITCZ during March-April is shown to be sensitive to relatively small variations in the Atlantic SST gradient. The effect of local ITCZ migration on precipitation in the Horn of Africa has been noted in a number of studies (e.g. Camberlin and Wairoto, 1997; Okoola, 1999; Camberlin and Philippon, 2002; Camberlin and Okoola, 2003), but it is important to consider the influence of ITCZ movement in other regions of the world, for example as a result of variations in the Walker circulation (Black *et al*., 2003; Chiang *et al*., 2002), on local ITCZ migration. A stalling of the ITCZ in the Pacific Ocean may propagate, delaying the northward migration of the ITCZ over Africa and hence exerting a strong influence on spring AAP totals. Riddle and Cook (2008) discuss the presence of abrupt precipitation transitions during March over Ethiopia, as the result of the ITCZ. Potentially, this precipitation transition may be partially attributed to the delayed migration of the ITCZ in the Pacific Ocean.

The tripole pattern appears similar to the structure of ENSO SST anomalies. ENSO variability has been linked to precipitation in more southerly regions of East Africa (Camberlin and

Philippon, 2002), and indeed to Ethiopian precipitation during the Kiremt (e.g. Segele *et al*., 2009). Previous work has identified links between the phase of ENSO and the position of the ITCZ. During a positive ENSO phase, for instance, the Pacific ITCZ is drawn toward the equator during spring by warmer equatorial waters, while conversely during a negative phase, the ITCZ is generally positioned further north. While the tripole pattern contains ENSO-related features,, clear differences emerge when considering the extent of particular features. For example, the area of positive correlation in the central Pacific becomes less intense towards the equatorial western coast of South America. Also, this area of positive correlation covers a greater spatial extent than the eastern central Pacific, reaching as far north as 30°N. Correlation analysis was undertaken in order to assess to what extent the link between Pacific SST and AAP can be captured by simple indices that describe variability in ENSO (Table 1). Our results show little relationship to exist between spring AAP and either Nino3.4 or Nino4, with the exception of a significant relationship between AAP and Nino 4 during February.

Additionally, the correlation pattern in the northern Pacific shares some characteristics with the Pacific Decadal Oscillation (PDO). Negative correlation in north-western parts of the Pacific basin is particularly notable for its similarity to the region of enhanced cyclonic circulation around the deepened Aleutian low associated with a positive, warm PDO phase (Liu and Alexander, 2007). In general, the correlation pattern suggests spring AAP to be heavier when associated with a positive phase PDO. However, in spite of the possible influence of the PDO, there is also no significant correlation between spring AAP and the century-long PDO index (Table 1).

The absence of a significant linear relationship between AAP and any of the simple indices show that the mechanisms linking Pacific SST to spring AAP cannot be explained purely by ENSO or PDO. However, given the prominence of the tripole pattern shown in Figure 4, there is scope to calibrate a prediction model based on patterns of SST anomalies within a bespoke spatial domain.

## 4. Potential predictability of spring precipitation

In this section we formulate and cross-validate regression models that estimate spring AAP from Pacific SST patterns. Potential for developing a seasonal prediction model exists if there are substantial correlations between AAP and Pacific basin SST at some lead time. The basic tripole structure of the non-lagged correlation patterns found in the central Pacific during February, March and April shown in Figure 4 can also be found for SST lags up to six months in advance; for lags up to three months the magnitude is similar to that of the concurrent patterns.

Linear regression models based on one-dimensional MCA and PC-MLR were developed to estimate spring AAP from Pacific SST at varying lead times. Spring AAP was also broken down into its component months, allowing for the strongest predictive relationship to be determined based on a predictand period of one or more months. When formulating such models, it is preferable to restrict the predictors to a region where the magnitude of the correlations, and thus predictive power of SST, is greatest. As the correlation patterns may depend on the lead time these and the resulting predictor domain have been calculated for each predictor-predictand combination. Each domain is chosen such that the domain is the smallest rectangle that includes all regions where the correlation magnitude is greater than ±0.3. Correlation maps for six predictand periods (February, March, April, February-March, March-April and February-April) in combination with SST lags of up to six months have been investigated.

Correlations between spring AAP and Pacific SST during the preceding three to four months are high enough to attempt fitting seasonal predictability models. The left-hand panels in Figure 5 show the correlations maps for four predictor-predictand combinations along with the most appropriate predictor domain determined for each. The pattern describing the relationship between February AAP and December Pacific SST (hereafter Feb:Dec) comprises much of the western Pacific, whereas those used to describe the Mar:Dec and FMA:Dec relationships take into account the southern and eastern Pacific. By contrast, the Apr:Jan pattern is constrained to a smaller region of the western equatorial Pacific associated with a clear SST gradient.

The leading three SST EOFs for each predictor domain and predictor month are shown in the remaining panels of Figure 5. In each case the structure of EOF1 is remarkably similar to the correlation maps which cannot be expected a priori and indicates that the Pacific SST anomalies that influence AAP are similar to the leading SST variability mode. The MCA and PC-MLR models are fully described by the effective weights that each predictor gridcell has in the final AAP estimate (Figure 6). As the estimated AAP is the projection of the SST anomalies onto these weight patterns they can be interpreted as the SST anomaly patterns that are most closely linked to AAP in the given regression model. For MCA, these weights are proportional to the regression maps while for PC-MLR they are the linear combinations of the EOF loadings with weights given by the regression coefficients of the PCs (Widmann, 2005). The regression maps, or the MCA weights, are the point-wise products of the correlation maps and the standard deviations of the SST field, and as a consequence the MCA weights in Figure 6 are very similar to the correlation maps shown in Figure 5. For the PC-MLR model 12 predictor PCs have been used, based on a maximisation of the cross-validated correlations between estimated and true AAP. This high number of predictand PCs is the reason for the relatively noisy PC-MLR weights compared to the MCA weights. Although the large-scale structure of the MCA and PC-MLR weight patterns is clearly similar there are also some notable differences which reflect how the identification of predictor SST patterns for AAP depends on the specific method chosen.

As mentioned in section 2 each reconstruction has been calculated and cross-validated using a leave-*n*-out technique (in this case, *n*=7). Figure 7 shows the observed AAP along with reconstructions based on MCA and PC-MLR models and the cross-validation correlations. In general, MCA does not reproduce temporal variability as well as PC-MLR, with correlations between observed and reconstructed FMA precipitation only reaching 0.24 (Figure 7e). By contrast, the PC-MLR models achieve correlations of greater than 0.4.

Placing these results in the context of previous work is difficult due to the paucity of studies that have focused on spring precipitation in Ethiopia. Diro *et al*. (2008) calibrated MLR models for estimating Belg precipitation based on Pacific SST anomalies but presented no direct quantification of temporal variability. Camberlin and Philippon (2002) focused on the potential predictability of spring precipitation in Ethiopia and other parts of East Africa (using Pacific SST indices as predictors); while MLR-based estimates for spring precipitation in the Kenya-Uganda region are reasonably correlated with observation (r = 0.66), a similar prediction model for Ethiopia is not considered feasible. While it is not possible to make a direct comparison with similar statistical models used to estimate summer precipitation, such results provide a basis upon which to judge the strength of our results. Gissila *et al*. (2004) found a correlation of 0.6 between observed and predicted summer (JJAS) precipitation, using Pacific and Indian Ocean SST for the previous season. Block and Rajagopalan (2007) used a linear modelling approach to estimate summer precipitation in the upper Blue Nile basin in north-east Ethiopia, and showed a correlation of 0.69 with the 1961-2000 observational record.

As discussed in section 1, much previous work has sought to establish predictability models using only a few decades of data. While the majority of records are of sufficient length to permit a fairly robust assessment of model skill in reproducing year-to-year variability, it is troublesome to extend such an assessment to decadal variability. The precipitation series used here is of sufficient length to address this issue. A five-year filter is applied to observed and estimated AAP (Figure 7, right panels). Estimates from both methods capture anomalous periods of spring AAP in the second half of the twentieth century, particularly the dry periods of the mid-1970s and the late-1990s. Conversely, the models in the earlier half of the time series are less effective; the dry periods falling between 1915 and 1930 are not captured by either model estimate. Under the five-year filter, both methods yield significant correlations for each predictor-predictand combination. While PC-MLR remains the stronger performer at interannual time scales, MCA shows similar skill when a five-year filter is applied. Given that MCA models are simpler to formulate due to there being no requirement for a pre-filtering step, this method may be preferable in reconstructing (sub-)decadal means.

We now investigate the processes that underpin the statistical relationships. As discussed in section 1, the mechanisms controlling spring precipitation, and their links to large-scale Pacific SST anomalies, are not fully understood. Variability in the migration of the ITCZ accounts for a large portion of interannual variability in Ethiopian precipitation (Seleshi and Zanke, 2004). It is understood that the spring months are associated with the southward shift of the ITCZ and the northward migration of the Arabian high (Baker *et al*., 2007). Such changes are likely to be driven locally by SST in the Indian Ocean, which in turn are known to be influenced by ENSO (e.g. Nagura and Konda, 2007; Annamalai *et al*., 2010).

In order to investigate how the SST patterns on which our statistical models are based are linearly related to large-scale atmospheric variability we correlated the estimated precipitation with mean sea level pressure, temperature and specific humidity from the ERA-40 reanalysis for the period 1958-2001. As the estimated precipitation is given by the orthogonal projection of SST anomalies onto the effective weight patterns it can also be interpreted as the TEC of the weight pattern or as the TEC of the SST anomaly most closely related to AAP by a given regression model. For brevity, only the Mar:Dec and FMA:Dec plots are shown but others are included in the discussion. Correlation with SLP is positive across the majority of the Indian Ocean and Africa, although there is little to suggest that the TEC series is strongly correlated with the strength of the Arabian high. In the case of the Mar:Dec PC-MLR model, the TEC series is in fact negatively correlated with SLP over the Arabian peninsula. As discussed in section 3.1, it is important to consider the intra-seasonal differences in the mechanisms controlling spring precipitation, and it is not unexpected that SLP correlation during March is different to that for the February-April mean. In general, the TECs show a positive correlation with both March specific humidity and temperature at 1000hPa over much of the western Indian Ocean, with magnitude greatest to the east of Madagascar. For specific humidity, this relationship persists at 850hPa at a smaller magnitude (not shown). For Feb:Dec, the correlation pattern is similar to the Mar:Dec pattern across the Indian Ocean, although the region of strongest positive correlation appears to the south-east of India. A similar pattern is evident in the Indian Ocean for the Apr:Jan reconstructions, although with a much smaller magnitude. Of particular note is the region of negative correlation between TECs (particularly, Mar:Dec MCA) and 1000hPa specific humidity over the northern Arabian Sea, which is a relationship consistent with previous findings (Camberlin and Philippon, 2002).

The correlations associated with the MCA model are substantially higher than those for the PC-MLR model. The likely reason is the fact that the MCA weight patterns (Figure 6) are similar to SST EOF1 (Figure 5), which essentially captures ENSO variability and thus is associated with strong teleconnections. This similarity of MCA weights and EOF1 is a well-known property of MCA that stems from the fact that the method maximises covariances. In contrast the PC-MLR weights (Figure 6) are less confined to the leading SST EOFs; they maximise the correlation of their TEC with AAP rather than capturing dominant global-scale variability modes.

The SLP anomalies for the models for March precipitations (Fig. 8a,b) can be directly compared with the SLP and wind anomalies for wet and dry composites for March (Fig. 2 c,d). In particular the SLP anomaly associated with the PC-MLR (Fig. 8b) shows clear similarities to the wet anomaly (Fig 2c), these include low pressure to the south-east of Madagascar and high pressure west of Australia, low pressure over southern and high pressure over central Africa, low pressure over the Arabic Peninsula and to the north of it and high pressure over India. The other SLP correlation patterns (Fig. 8 a,c,d) are similar in structure and thus still quite similar to the wet SLP anomaly, but to a smaller degree. This suggests that the Pacific SST anomalies used in our statistical models are linked to AAP because they are associated with SLP and thus with wind anomalies that are strongly linked to AAP variability. It seems not clear to what extent these SLP anomalies are linked to changes in the position of the ITCZ or more general to changes in the Hadley and Walker Circulation and a detailed analysis is beyond the scope of this study.

The humidity and temperature anomalies (Fig. 8 e-l) can be partly understood as advection patterns associated with the SLP anomalies. This is for example the case for the warm-cold and moist-dry dipoles in the south-east part of the domain, as well as for the temperature and moisture anomalies over Ethiopia (cf. wind anomalies in Fig 2c,d). The nature of the link between the anomalies in the different variables over the equatorial Indian ocean is however not clear.

## 5. Summary and conclusions

In many parts of East Africa great strides have been made in the last two decades in understanding the governing mechanisms behind monthly and seasonal precipitation. In the case of Ethiopia, the traditionally heavy Kiremt rains of the summer months have received the majority of research focus, but there remains much to be understood about the regional- and large-scale controls on the preceding Belg rains during spring. Here, we have identified linear links between interannual variability in Pacific SST and spring precipitation in Addis Ababa, Ethiopia and have formulated and assessed regression-based prediction models for AAP with lead times of several months using Pacific SST as a predictor.

The main conclusions can be summarised as follows:

1. Spring precipitation exhibits a contemporaneous linear relationship with basin-wide Pacific SST. Although the correlation patterns have a tripole structure that broadly resembles ENSO and PDO SST anomalies, the patterns describe links independent of ENSO and PDO, as the ENSO and PDO indices are only very weakly correlated with AAP.
2. A relationship similar in spatial extent and magnitude also exists between spring AAP and Pacific SST during the preceding boreal winter (December and January), providing a basis for calibration of linear regression prediction models.
3. Using cross-validation, moderate skill was found for MCA and PC-MLR prediction models with a generally better performance for the PC-MLR models.
4. The highest skill was found for PC-MLR models that link December SST to AAP in February ($r = 0.48$), March ($r = 0.40$) and February to April ($r = 0.44$).

5. The Pacific SST anomalies that are the basis for the reconstructed AAP are associated with large-scale anomalies in SLP, wind, temperature and specific humidity, which in turn are linked to moisture and precipitation anomalies over East Africa.
6. The relationships between Pacific SST in December and AAP during spring seem strong enough to lead to practically useful forecasting models for the Belg rains. Further analysis may focus on drought forecasting using ROC and RPSS metrics taking tnto account the error variance of the regression models.

## Acknowledgements

HadISST data provided by the Hadley Centre at the UK Meteorological Office, and accessed from the NCAS British Atmospheric Data Centre.

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**Table 1:** Correlation of spring AAP with PDO (1900-2004), Nino 3.4 and Nino 4 indices (1950-2004); p-values shown in parentheses.

| | **Feb** | **Mar** | **Apr** | **May** |
|---|---|---|---|---|
| **Nino 3.4** | 0.29 (0.04) | 0.14 (0.31) | 0.14 (0.33) | -0.01 (0.94) |
| **Nino 4** | 0.07 (0.61) | 0.15 (0.28) | 0.08 (0.56) | 0.06 (0.65) |
| **PDO** | 0.11 (0.26) | 0.13 (0.21) | 0.09 (0.34) | 0.14 (0.16) |

**Figure 1**: Topography map of Ethiopia, indicating the location and precipitation characteristics of Addis Ababa.

**Figure 2**: Spring (FMAM) mean 1000hPa wind and SLP (hPa) in ERA-40 (1958-2001).

**Figure 3**: Spring (FMAM) 1000hPa wind and SLP (hPa) anomalies in ERA-40 during the five (a-d) wettest and (e-h) driest months (1958-2001).

**Figure 4**: Correlation between spring (FMAM) AAP and concurrent SST. Correlation is significant ($p$<0.01) where stronger than ±0.25.

**Figure 5**: Correlation between AAP and lagged Pacific SST, with rectangular domain of predictability shown (left panels; left colour bar); and eigenvector spatial patterns of Pacific SST of the leading three EOFs within each domain (remaining panels; right colourbar).

**Figure 6**: Effective weights in MCA (left panels and colourbar) and PC-MLR (right panels and colourbar) models.

**Figure 7**: Observed (solid lines) and cross-validated AAP reconstructions based on MCA (dashed lines) and PC-MLR (dotted lines). Left panels show precipitation anomalies with reference to the 1900-2004 mean; right panels show 5-yr filtered precipitation. Correlation coefficients for MCA ($r_M$) and PC-MLR ($r_P$) are shown with associated *p*-values in parentheses.

**Figure 8**: Correlation of reconstructed March only and February-April AAP with concurrent ERA-40 sea level pressure (slp), and specific humidity (q) and temperature (t) at 1000hPa (1958-2001).