Seasonal Climate Predictability in Ethiopia:
Review of best predictor sets for sub-seasonal to seasonal forecasting

Working Paper No. 301

CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS)

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Abstract

As elsewhere in the Tropics, the climate of Ethiopia is highly variable. Capturing its variability has been a major challenge for climate models and tools. Understanding teleconnections and predictors is, therefore, an important step towards improving the skill of seasonal and intra-seasonal climate forecasts, derivative products such as seasonal yield predictions, and climate services in general. This report presents a review of existing knowledge on teleconnections, climate predictability and seasonal to intra-seasonal climate forecasting advances and challenges for Ethiopia. Literature reviewed indicates an association between the seasonal climate of Ethiopia and seas surface temperature (SST) forcings over the Atlantic, Indian Oceans and, to a greater extent, over the equatorial Pacific along with associated atmospheric circulations. The main (*Kiremt*) season's climate is strongly influenced by teleconnections with SST anomalies and the El Nino Southern Oscillation (ENSO) in the Nino-3.4 region of the equatorial Pacific and can yield moderate skill forecasts with 1 to 2 month lead time, while the Indian Ocean Dipole (IOD) has relatively stronger influence on the climates of the dry season (*Bega*) and small rains season (*Belg*). Best climate predictors and prediction skill therefore vary for the different seasons of Ethiopia. The procedures and methods used by the National Meteorology Agency (NMA) of Ethiopia to forecast seasonal and intra-seasonal climates and their pros and cons are discussed.

Keywords

Seasonal climate predictability; Forecasting skill; Teleconnections; Ethiopia.

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Acronyms

AGCM	Atmospheric General Circulation Model
CCA	Canonical Correlation Analysis
CHIRPS	Climate Hazards Group Infrared Precipitation with Stations
CPC	Climate Prediction Center
CPT	Climate Predictability Tool
ENSO	El Nino Southern Oscillation
ERSST	Extended Reconstructed Sea Surface Temperature
GCM	General/Global Circulation Model
GeoCOF	Geospatial Climate Outlook Forecasting Tool
IOD	Indian Ocean Dipole
ITCZ	Inter Tropical Convergence Zone
JAS	July, August and September
JJAS	June, July, August and September
MAM	March, April and May
MLR	Multiple Linear Regression
LDA	Linear Discriminant Analysis
NMA	National Meteorological Agency
NOAA	National Oceanic and Atmospheric Administration
MME	Multi-Model Ensemble
RCOF	Regional Climate Outlook Forum
SLP	Seal Level Pressure
SOI	Southern Oscillation Index
SON	September, October and November
SST	Sea Surface Temperature

SSTA	Sea Surface Temperature Anomaly
RSCZ	Red Sea Convergence Zone
TEJ	Tropical Easterly Jet
WMO	World Meteorological Organization

Introduction

Mankind recognized millennia ago the importance of climate variability for the sustenance of life, whether that variability was expressed in the form of droughts, floods, heat, cold, or wind. Coping strategies developed to handle the consequences of climate variability helped ensure the survival of mankind, although the historic record indicates that not all civilizations successfully overcame past challenges imposed by long-term droughts, extensive flooding, and the like. Much has changed in the modern era, with coping strategies such as migration, invasion and appropriation frequently constrained by international boundaries and laws. Included amongst the technological advances that have led to increased resilience against climate variability are remarkable achievements in the understanding, monitoring and prediction of climate variability itself (Troccoli, 2008).

In principle, modern seasonal to inter-annual predictions are an answer to the needs of many whose activities are influenced in some manner by climate variability, whether in terms of creating profit through the marketing of an appropriate range of goods, or for critical decisions regarding agriculture and food security. From a practical perspective, there is only one reason for undertaking research and development to advance seasonal climate predictions and for investing in the infrastructure to produce and deliver them. That reason is to assist whatever decision processes are of concern to those who might make use of them. For that matter, prediction information must be reliable to be admissible into the decision processes of recipients (WMO, 2002).

The idea that the climate may be predictable at seasonal timescales may seem counterintuitive, given that weather does not appear to be predictable with much accuracy beyond a few days. At seasonal scale, the errors become so large that there is no longer a forecast, but an accidental resemblance between the forecast and the observed conditions. However, it is possible to provide information, based on a different source of predictability (Hansen et al., 2011). Changes in the earth's surface, particularly sea surface temperatures (SST), can influence the atmosphere. Since ocean temperatures tend to change slowly relative to the atmosphere because of their high heat capacity, knowing the current state of the oceans may provide some degree of predictability on seasonal time scales. Thus, while it is harder to forecast the weather in the Tropics, it tends to be easier to predict the seasonal conditions, although predictability at seasonal timescales is highly dependent on location and on the time of the year (Troccoli, 2008).

It is important to note that average circulation in the tropics is, on the one hand, a major characteristic of the atmospheric variability and, on the other hand, strongly influenced by the large scale organized convection (notably the Walker-Hadley divergent circulation), the latter being strongly controlled by the evolutions of the conditions of oceanic and continental surfaces. That particularly explains why seasonal forecasting has enhanced scores and skills in tropical areas compared to the mid-latitude regions. In addition to solar forcing, the principal source of energy for the climatic system, one can distinguish between continental and oceanic forcings. SSTs are particularly used in both coupled and forced numerical models, but also in the majority of statistical models. This information coming from the oceanic surface allows us to get reasonable forecasts up to a lead time of 4 months. Beyond, information from coupled Ocean-Atmosphere dynamics is typically required, using general circulation models (GCM) including sub-surface information. The best known of these forcings is related to the El Niño Southern Oscillation (ENSO), with planetary consequences (Clarke, 2008).

Ethiopia, like many parts of the Tropics, is prone to extreme climate events such as droughts and floods. In an effort to minimize the negative impacts of extreme climate events, and to better exploit opportunities offered by climate, in 1980 the Government of Ethiopia established the National Meteorological Services Agency (currently, National Meteorological Agency; NMA). Today, NMA uses a statistical method based on analogue multivariate ENSO index years. The outputs of this method are probabilistic categorical forecasts of regional Ethiopian rainfall (Korecha and Sorteberg, 2013). The goal of this review is to review and discuss current knowledge concerning predictability and predictions of Ethiopian seasonal climate. In this review, we focus on assessing the current practices, methods and tools used to produce seasonal climate forecasts by NMA.

The Seasonal Climate of Ethiopia

Meteorologically, a season is a period when an air mass characterized by homogeneity in temperature, humidity, wind patterns, rainfall, etc., influences a region (Désalmand, 1998). Ethiopia's rainfall climatology is mainly determined by seasonal changes in large-scale circulation, part of which involve the latitudinal movement of the intertropical convergence zone (ITCZ) as happens throughout the larger Sahel region from Sudan to Senegal (Nicholson 1989). In Ethiopia, seasons are unique and are classified mainly based on rainfall and its distribution.

"*Bega*" is a generally dry season that covers the period from October to January. During this season, Ethiopia is predominately influenced by both warm and dry air masses originated from the Saharan Anticyclone as well as cool and dry air masses originated from the Siberia and Arabian Anticyclones. However, associated with occasional eastward movements of mid-latitude depressions, the Arabian high can displace and establish itself over the Arabian Sea. In such situations, the interaction between the southeast warm moist and mid latitude cool dry air masses, coupled with mid-tropospheric deep troughs and with the Subtropical Jet (STJ) can produce substantial and untimely rains.

The **"*Belg*"** season refers to a small rainy season that covers the period from Mid-February to Mid-May. This season coincides with the dominance of the Arabian high as it moves toward the North Arabian Sea. In this season a thermal low develops over Sudan, an anticyclone forms over the Arabian Sea, and resulting easterly winds bring considerable amounts of moisture to the region under consideration. Sometimes the Northern part of the region is under the influence of the warm and dry Sahara and Arabian air masses. In general, the weather systems that are responsible for rainfall activities during the *belg* season are:

- The development of high pressure over the Arabian Sea;
- The generation and propagation of disturbances, sometimes coupled with Easterly Waves;
- The interaction with mid- latitude depressions accompanied by trough and STJ, the tropical disturbances and ITCZ; and
- The occasional development of Red Sea Convergence Zone (RSCZ), which produces substantial rainfall in the Northeast parts of the region.

"*Kiremt*" refers to the main rainy season that covers the period from June to September. Airflow during this season is dominated by a zone of convergence in low-pressure systems accompanied by the oscillatory Inter-tropical convergence zone (here after ITCZ) extending from West Africa towards India through Ethiopia or North of it. The major rain-producing components during *kiremt* are:

- The northward Migration of ITCZ following the sun's movement;
- The development and persistence of the Arabian and Sudan thermal lows along 20$_{o}$ latitude;
- The development of the Quasi-high-pressure system over the Southern Atlantic and Indian Ocean
- The development and persistence of the Indian sub-continent's depression and the associated Monsoon trough; and
- The development of the tropical Easterly jet stream (TEJ) and its persistence for distribution and intensity of rain.

The National Oceanic and Atmospheric Administration (NOAA) defines the ENSO state (e.g., El Niño or La Niña) as a departure of magnitude 0.5°C or more from normal SST in the Niño 3.4 region, lasting for at least five running three-month periods over the tropical Equatorial Pacific Ocean. The main ENSO signal is found during the northern summer (Camberlin, 2009) at which time a negative correlation is found with the Niño 3.4 index, depicting lower than normal rainfall in the years of higher sea-surface temperatures (SST) in the eastern equatorial Pacific (i.e., El Niño years). It is argued that each ENSO state (El Niño, neutral or La Niña) has its own influence on the rainy or dry season.

The physical connection between these changes in the atmospheric general circulation and ENSO is complicated and not well understood. Other factors such as southern Atlantic and Indian ocean SSTs also influence the rain-bearing systems in Ethiopia. Not all ENSO events correlate directly with drought in Ethiopia. The 1982-83 El Niño, for example, did not cause failure during the (*kiremt*) main rainy season *strictu senso* although one of the worst droughts in Ethiopian history occurred over 1983-84 (NMSA, 1996). Despite this complexity, Ethiopian researchers have developed a system for identifying when an El Niño event is likely to produce climatic variations in Ethiopia, and for forecasting ENSO-induced climate anomalies. The NMA of Ethiopia, based on criteria that define particular types of ENSO events, has concluded that negative SST anomalies are strongly associated with below-normal rainfall during *belg*; positive SST anomalies are often correlated with good rainfall during *belg*, while the effects are opposite for the main rainy season (*kiremt*).

ENSO events are always associated with the overturning of the Walker cell, such that the descending limb of the cell rather than the ascending limb sits over Africa.

Atmospheric dynamics responsible appear to be causing cold air outbreaks from the Siberian High area. To the east of the Tibetan Plateau, over the western Pacific between Japan and Philippines at about 13E a quasi-stationary upper level westerly long wave trough with a length around 500km is maintained during *bega*. Through this trough, the short-wave disturbance in the form of cyclonic vortices travels. During ENSO the effect of this to start instance period of eastward moving of extra tropical systems across the Mediterranean areas and its trough move toward the equator at 40 $_{o}$E. This indirectly makes warm and moist air to be pumped to the North and central part of the Ethiopia resulting in warmer and wetter condition than normal. In addition, during this season the Red Sea convergence zone (RSCZ) intensifies during ENSO years. This abnormal rain occurs during the harvesting season and may reduce annual crop yield product both in terms of harvest volume and quality. El Niño affects the *bega* season in such a way that it makes the season wetter than normal. Hence, during *bega*, El Niño (positive SSTAs) is correlated with normal or above normal rainfall.

The impact of La Niña over the *bega* season is negative. La Niña makes the *bega* season extremely dry. Depressed atmospheric water vapor hampers cloud formation, and due to enhanced nocturnal emissions (night-time long wave radiation) minimum temperatures tend to decrease, resulting in frost conditions over some highland areas.

Potential Predictability of Ethiopia's Seasonal Climate

Predictability of Kiremt and Belg Season Climate

Given that the atmosphere is predominantly heated from the earth's surface rather than directly from the sun and given that the atmosphere receives its moisture from the earth's surface, changes in the earth's surface, particularly the SST distribution, can influence the atmosphere. There are significant interconnections between the surface temperature of the oceans and the associated atmospheric circulation due to heat transfers from oceans to the atmosphere. Any significant departure of the earth's surface from its normal conditions can disrupt weather patterns over a prolonged period. These disruptions are likely to be strongest in the Tropics where sea surface temperatures are warmest. Since ocean temperatures tend to change slowly relative to the atmosphere because of their high heat capacity, knowing the current state of the oceans may provide some degree of predictability of how weather patterns may be disrupted. The basis of this burgeoning industry is that slowly varying components of the geosystem, most significantly SST across tropical ocean basins can impart a ‘memory’ to the atmosphere in the vicinity of any such long-lived anomalies. To the extent that this ‘memory’ can be transmitted to parts of the globe remote from the originating sea surface temperature anomalies (SSTA), meteorologists refer to this phenomenon as teleconnections (Rosenzweig and Hillel, 2008).

The inter-annual variability of the seasonal mean in the tropics is mainly determined by slowly varying components such as SST, albedo, sea ice, and soil moisture. Model experiments showed that the tropical circulation and precipitation are strongly determined by the underlying SST with very little sensitivity to the changes in the initial conditions of the atmosphere. The ENSO is the best-known example of a slowly varying phenomenon that results from ocean-atmosphere interaction in the tropical Pacific. The prediction of conditions associated with ENSO has also seen more success in seasonal prediction by the climate forecasting community.

Since Ethiopia is located within the Tropics, seasonal predictability is higher compared to mid-latitude countries. The Ethiopian seasonal climate shows significant year-to-year variations. One of the important mechanisms that control this year-to-year variability is the ENSO state. Thus, the ENSO condition and the associated SST pattern is the primary source of predictability so far. The impact of ENSO on Ethiopian seasonal climate and its potential for predictability is widely documented. Sir Gilbert Walker was the first to indicate indirectly the presence of a link between the Southern Oscillation and rainfall variability in parts of Ethiopia. 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 Highlands (Walker and Bliss, 1932). The first experimental seasonal forecast based on El Niño effects was made in 1987 by NMA.

Previous studies have identified the role of remote SST forcings over the Atlantic, Indian, and to a greater extent, equatorial Pacific Oceans and the associated atmospheric circulation over the Ethiopian seasonal climate (Table 1). The *Kiremt* seasonal climate variability can be strongly influenced through teleconnection patterns originated by SST anomalies in the Nino-3.4 region of the equatorial Pacific. For instance, (Gissila et al., 2004) used empirical methods to predict *Kiremt* rains, using the relationship between SST data for March, April and May in the Indian and Pacific Oceans. The most extensive study of the predictability of the *Kiremt* rains is that of Korecha and Barnston (2007). This study investigates the strength of linear relationship between all Ethiopian *Kiremt* rainfall and the Niño-3.4 SST index derived from Extended Reconstructed Sea Surface Temperature version 2 (ERSSTv2). The association of summer rainfall with ENSO in early pre-summer months (January–April) is weak and increases as the ENSO state approaches the beginning of the rainfall season. The correlation is moderate (-0.59) for the May Niño-3.4 SST, suggestive of some predictability based solely on the May ENSO state.

The polarity of the ENSO teleconnection depends on the season in question with positive SST anomalies in the eastern Pacific (El Niño) being associated with rainfall deficits in the *Kiremt* season and excess rainfall in the *Belg* season. The ENSO signal on observed *Belg* rainfall anomalies over southern Ethiopia seems to be weaker than for *Kiremt*. (Diro et al., 2008) identifies various regions of SST anomalies over Atlantic, Indian and Pacific Ocean to predict the *Belg* rains (Annex Fig. 7.1). Because of the spatial variation across Ethiopia in both interannual variability and the annual cycle, Diro et al. (2008) identified five homogeneous rainfall zones within Ethiopia and produced separate forecast models for each zone. Both multiple linear regression and linear discriminant analysis were applied to four sets of predictors. It was also shown that the models had the most skill in the southern and eastern parts of Ethiopia and that the extreme years were more reliably forecasted than the average years.

Predictability of Bega Season Climate

Interannual variability of *Bega* rains over south-eastern Ethiopia is dominated by large-scale changes in the Indian Ocean and its coupled atmosphere with a clear link to the Indian Ocean dipole (IOD). *Bega* rainfall over south-eastern parts of Ethiopia is increased during positive IOD events. Bahaga et al. (2015) explored the predictability of *Bega* rains in their Atmospheric General Circulation Model (AGCM) ensemble experiments and found a substantial potential prediction skill associated with East African short rains, given the predictability of SST anomalies over the Indian Ocean. Besides, a temporally limited potential for the dynamical predictability of short rain has been indicated using a coupled ocean–atmosphere general circulation model (Behera et al., 2006). They showed that the July–August signal of the IOD in the SST dipole mode index has a high prediction skill for the variability in *Bega* rains.

Recent Developments on Climate Predictability

More often, preceding month SSTA and ENSO state are the key operational predictors in Ethiopia. Yet, Nicholson (2015, 2014) argues that atmospheric variables (zonal and meridional wind and vertical motion) generally provide higher forecast skill compared to surface variables (SST and season level pressure, SLP) on shorter lead forecasts (1-month lead time). Hence, ENSO and IOD provide less forecast skill than atmospheric variables associated with them. Surface variables become somewhat more important for 2-month lead-time, longer-lead forecasts.

A well improved ensemble-based multiple linear regression technique is developed to assess the predictability of regional and national *Kiremt* rainfall anomalies and local monthly rainfall totals for Ethiopia (Segele et al., 2015). The ensemble prediction approach captures potential predictive signals in regional circulations and global SSTs, two to three months in advance of the *Kiremt* season. This ensemble features an improvement in terms of skill and usability compared to previous studies.

Table 1. Sources of predictability for the seasonal climate of Ethiopia

No.	Predictand	Predictors	Location	Prediction method and skill	Reference
1	*Kiremt* rainfall totals over homogeneous zones	Sea Surface Temperature	▪ Tropical western Indian Ocean (10 °S - 10 °N, 50 - 70 °E) and (10 °S -equator, 90 - 110 °E). ▪ The Niño-3.4 (5°S - 5 °N, 120 - 170 °W).	Multiple linear regression [r =0.6]	Gissila et al. (2004)
2	All Ethiopian Average *Kiremt* rainfall totals	Sea Surface Temperature	▪ The difference of May minus February to March SSTs over the south Atlantic (30° - 40°S, 15° - 30°W). ▪ The difference of May minus the February to March Niño-3.4 SST ▪ May Niño-3.4 SST	Multiple linear regression and Canonical Correlation Analysis [r=0.73]	Korecha and Barnston (2007)
3	*Belg* rainfall totals over homogeneous zones	Sea Surface Temperature	See Annex Fig.7.1 for details	Multiple linear regression (MLR) and linear discriminant analysis (LDA)	Diro et al. (2008)
4	JAS rainfall	Atmospheric and Oceanic Indices	See Annex Table 7.1 for details	Multiple linear regression (Annex Table 7.2 and 7.4)	Nicholson (2015, 2014)
5	MAM rainfall	Atmospheric and Oceanic Indices	See Annex Table 7.1 for details	Multiple linear regression (Annex Table 7.3)	Nicholson (2015, 2014)
6	September-October-November (SON) rains	Coupled operational seasonal forecast models (GCMs)	1-month lead IOD index	Multi-model ensemble (MME)	Bahaga et al. (2016, 2015)

Operational Seasonal Climate Forecasting at NMA

Ethiopia started issuing seasonal forecasts in 1987, ten years before the first RCOF. The NMA issues seasonal forecasts 3 times a year targeting the *Bega*, *Belg* and *Kiremt* seasons, 1–2 weeks prior to the normal onset date of each season. During early stages, the methods of forecasting used by the NMA are based on analogue, trend analysis (short-term trends of SST), statistical assessments, and teleconnections (Bekele, 1997). However recently the agency adopted a consensus seasonal climate outlook based on guidance from various prediction methods and tools. The seasonal climate outlook includes forecast information beyond seasonal rainfall totals, such as outlooks on the start, end and duration of the rainfall season. In addition, the agency forecasts several additional agriculturally important variables such as moisture status, water requirement satisfaction index and vegetation condition. The agency also issues outlooks on climate suitability for malaria transmission (Connor et al., n.d.).

Although there are various attempts to include a number of methods and tools to produce the seasonal climate outlook, the main method includes a combination of the analogue method and regression based statistical forecasting tools. The procedures of producing consensus-based seasonal climate outlooks at NMA include:

A. Diagnosis: involves examining temporal evolution and current status of oceanic and atmospheric synoptic scale regional and global meteorological features;

B. Prognosis: involves examining outlooks produced by global forecasting centers of the status of oceanic and atmospheric meteorological features on synoptic, regional and global scales (Figure 1).

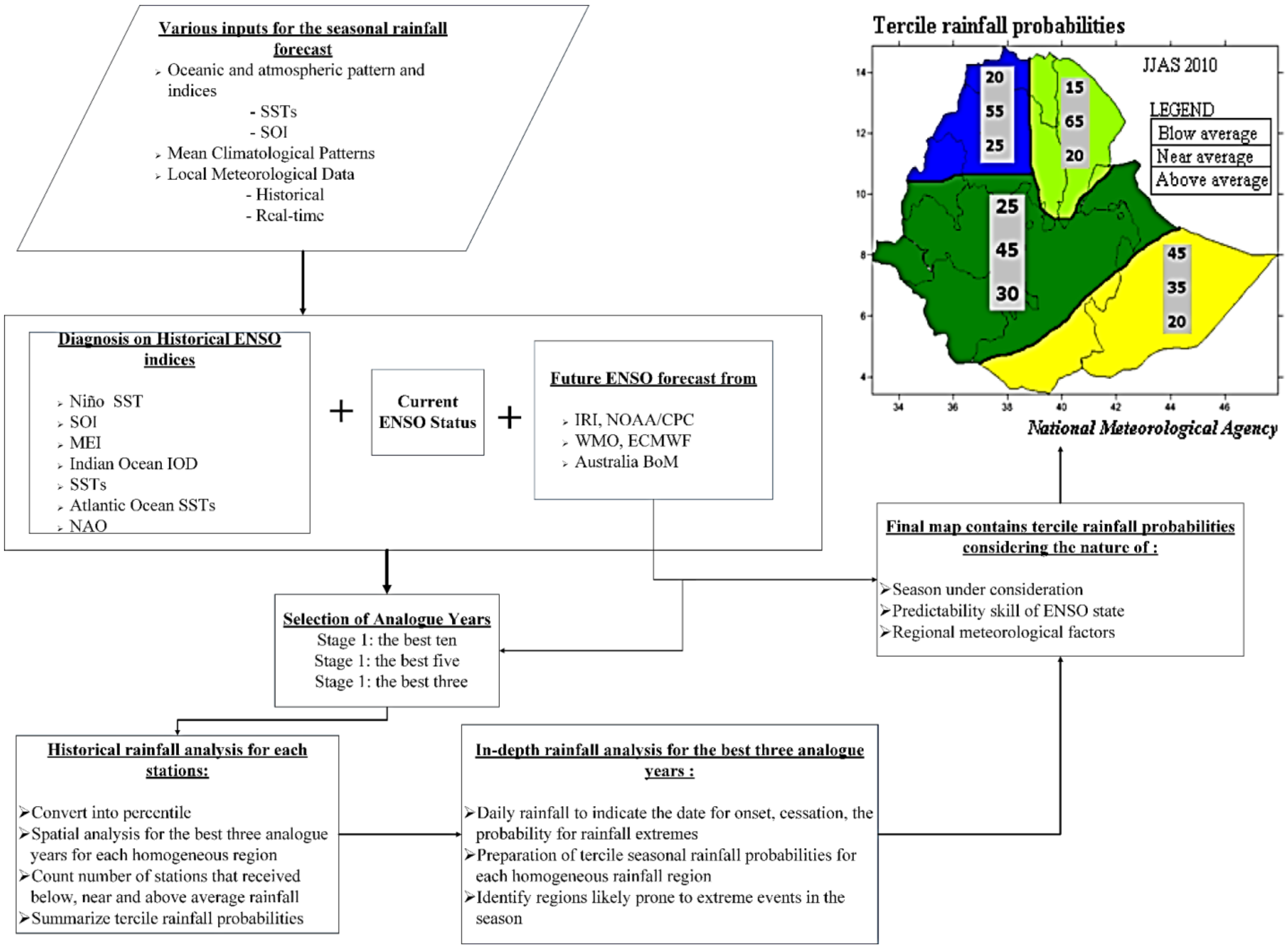

Figure 1. Schematic of the analytical steps in the preparation of seasonal rainfall forecasts by the National Meteorological Agency of Ethiopia (after Korecha and Sorteberg, 2013)

NMA uses indices of sea surface temperatures (SSTs) over the tropical Pacific Ocean, the Southern Oscillation Index (SOI), the Multivariate ENSO Index (MEI: Wolter and Timlin, 1998) and the ENSO outlook obtained from NOAA/CPC. Historical and current Niño 3.4 SSTs (located in the central equatorial tropical Pacific Ocean) are used to select years with an ENSO evolution similar to the current year.

NMA's seasonal rainfall forecasts are then prepared as a probability of the regional seasonal rainfall being below, near, and above the climatological normal for eight homogeneous rainfall regions (Figure 2). The classification is based on typical rain-producing systems affecting the region and on spatial and temporal response of each respective region to major atmospheric and oceanic circulation systems. Although some authors (Diro et al., 2010, 2008; Gissila et al., 2004; Tsidu, 2012) have proposed modifications to the NMA homogeneous rainfall regions, NMA still uses the originally defined eight rainfall zones for the preparation of seasonal forecasts. The tercile rainfall categories, which are more commonly known as the probabilities, refer to the likelihood that the region averaged rainfall will be below, near, or above average as the anomalies in seasonal (4-month) rainfall are often large in geographical scale.

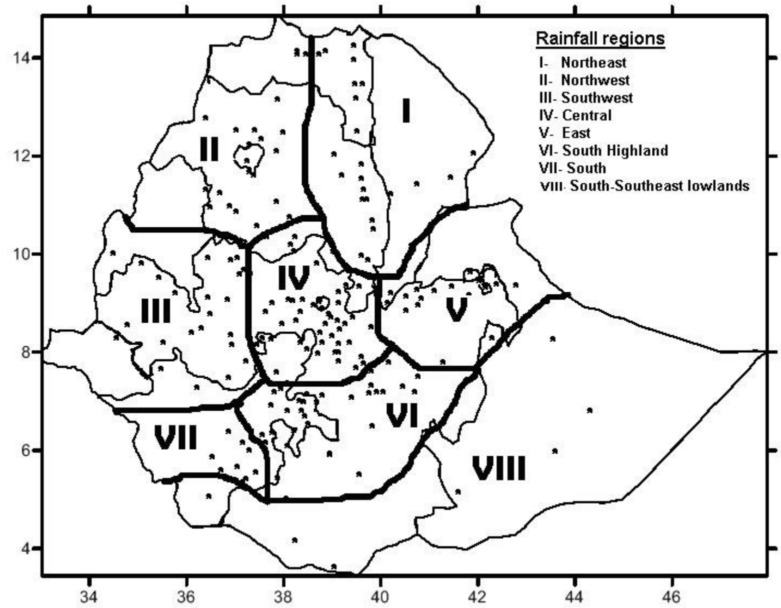

Figure 2. Homogeneous rainfall regions currently used for the preparation of seasonal rainfall forecasts in Ethiopia.

The Analogue Method

The analogue forecast methodology is one of the major techniques operationally used by NMA to produce seasonal forecasts. This technique involve an analysis of historical data in search of previous periods that resemble the immediate past period, and predicting the following season's rainfall anomalies on the basis of what happened on those previous occasions. In identifying the predictors for Ethiopia rainy seasons, previous research guides the selection of the most appropriate predictors from the historical archives. Various teleconnection patterns are linked to Indian, Atlantic, and Pacific Oceans, where they produce different climatic anomalies in various parts of Ethiopia (Gissila et al., 2004; Korecha and Barnston, 2007; Segele and Lamb, 2005; Shanko and Camberlin, 1998) . ENSO-indices have been well identified as the potential preseason indicators and thus have become the basis for analogue forecasting in Ethiopia. ENSO indices are being retained year round, but allowing these indices to be weighted differently from season to season as well as from region to region, depending on the direct linkage between regional rainfall pattern and SST anomalies.

The analogue approach requires the selection of 3 to 5 analogues years with an ENSO evolution similar to the target year, by comparing historical and target years' SSTAs in the Niño 3.4 region. The seasonal rainfall forecast for the target season is then prepared based on rainfall observed in these analogue years. The seasonal rainfall total of each station is expressed as a seasonal rainfall percentile and used to calculate tercile categories (0–33, *below*; 34–66, *near*, and 67–100%, *above* the climatological normal) for each homogeneous rainfall region.

The major advantage of the analogue forecasting technique currently used in NMA is that the climate information consists of past observations, so the implications can be readily connected with decision models and can be utilized in situations where the computing facility is very weak. Because of its conceptual simplicity, already identified various teleconnection patterns can be easily related to the observed climate to produce the seasonal forecast. This provides a unique opportunity for NMA to issue timely early warnings on the adverse effect of climatic anomalies within a reasonable lead-time.

Although the analogue method is simple and computationally efficient, it is limited by observational data and mostly depend on linear relationships. Non-stationarity due to decadal/multi-decadal climate variability is thus not considered (Goddard et al., 2010). Changes in observed mean, variability, and trend due to the changing climate and the associated unprecedented situations severely limit the usefulness of analogue approaches.

The Climate Predictability Tool (CPT)

The Climate Predictability Tool (CPT), developed by the International Research Institute on Climate and Society, provides a package for constructing a seasonal climate forecast model, performing model validation, and producing forecasts given updated data (Mason, 2011). Although the tool is specifically tailored for these applications, it can be used in more general settings to perform canonical correlation analysis (CCA), principal components regression (PCR), or multiple linear regression (MLR) on any data, and for any application. The Climate Predictability Tool (CPT) is an easy to use package for making tailored and downscaled seasonal climate forecasts. CPT is designed to produce statistical forecasts of seasonal climate using either the output from a GCM, or empirical predictors.

The underlying goal in using the CPT has been to address the widespread creation and communication of quality-controlled seasonal climate forecasts that address specific needs of different user groups. There are two main approaches to generating seasonal forecasts: using large-scale models of the global atmosphere, known as general circulation models (GCMs), or using a statistical approach to relate seasonal climate to changes in sea-surface temperatures, such as those associated with El Niño, or to other predictors. In the former case, predictions are made for large-areas, and are often not very relevant for specific locations. In addition, because of the coarse scale at which the GCMs operate, the geography in the models is often distorted, and so geographical locations can be displaced. These GCM outputs therefore need to be adjusted so that they can be applied at the local level. The CPT tool is designed to perform both forms of prediction, namely downscaling of GCM output, and purely statistical predictions.

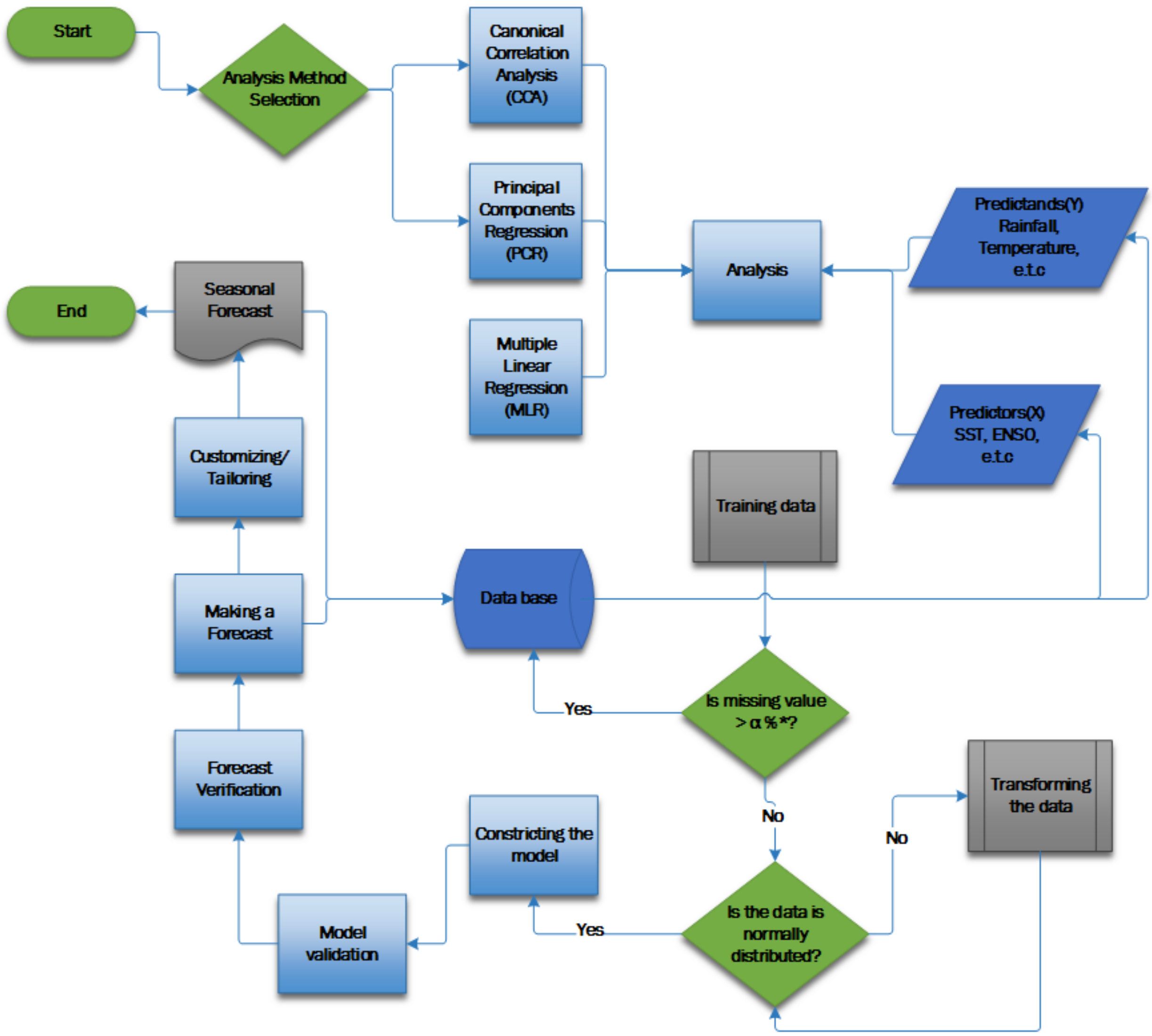

Figure 3. Methodological framework to produce seasonal forecasts using CPT

The Geospatial Climate Outlook Forecasting Tool (GeoCOF)

The Geospatial Climate Outlook Forecasting Tool (GeoCOF) is a statistical tool, developed by FEWS NET for producing probabilistic seasonal forecasts for rainfall and other climatic parameters. GeoCOF facilitates multiple-linear regression modeling, identification of potential predictors (e.g. regional sea surface temperatures) and forecast model skill assessments. Graphical outputs are designed to support regional climate outlook forums, such as through presentation of forecasts using tercile categories and maps (Magadzire et al., 2016).

GeoCOF uses observed SST data to forecast rainfall in a given homogeneous region. At the beginning, the datasets are summed up over the forecast period of interest, for example, monthly data can be summed up over Jun-July-August-September (JJAS) period in order to generate a time-series of JJAS totals. The JJAS totals are then converted to a standard normal variable (Z-score). The predefined homogeneous rainfall zones are used to summarize the predictand (rainfall) variable, allowing the rainfall for each zone to be correlated to potential predictors, especially oceanic regions that display a high correlation between their SSTs and rainfall. This allows the correlations between rainfall and SST to be analyzed, and ultimately for a regression-based forecast model to be developed for each climate zone.

The SST data aggregated from the oceanic regions that are well correlated with rainfall is selected. In doing so, very small regions should be avoided as these are not robust in analysis. Oceanic regions whose correlation with the rainfall zone of interest is difficult to explain should also be avoided as predictors. Different combinations of potential predictors are then tested using a number of statistical tests to identify the best statistical models that can be used to predict the climate variable of interest.

A linear regression model is produced using the NOAA Extended Reconstructed Sea Surface Temperature (ERSST) v4 monthly lagged SST values as predictor and the Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) dataset as predictand data. The regression model can be developed using either a single month SST, as available in the GeoCLIM ERSST database, or using multiple months, such as 3-month averaged SSTs. The established regression model is trained using the data from 1981 to 2010. The regression model is refined with the remainder of the historical rainfall and SST fields using the error variance of the cross-validated forecasts over the training period. Once a satisfactory model is identified, the current observed SST value of the predictor then substituted into the regression equation to make a forecast.

Conclusion/recommendations

This review provides an overview of the current state of knowledge and operations with regard to seasonal climate forecasting in Ethiopia. Most of the studies reviewed agree that potential predictability with moderate skill is achievable by exploiting the equatorial Pacific SSTAs, particularly in the Niño-3.4 region and the associated ENSO state. For this oceanic region, the ENSO predictive skill is higher during May (the preceding month) for the *Kiremt* season. This is the approach followed by NMA. SSTAs over the Atlantic Ocean (Gulf of Guinea), the Indian Ocean, and the associated IOD could provide additional sources of predictability, particularly for the *Bega* and *Belg* seasons. Clearly, strategic and tactical decisions could benefit from seasonal predictions on longer time scales, such as 2 to 3 month lead forecasts which may be improved using multivariate indices combining oceanic and atmospheric predictors. Some recent studies proposed indeed that atmospheric variables such as low-level and upper level winds could provide greater predictability than surface variables. The merit of this idea stems from the association between patterns of tropospheric convergence, divergence and vertical motion (which provide the direct forcing) and the dominant stability mechanisms in the region. Finally, the demonstration of the predictability of climate by CGCMs using multi-model ensemble approaches brings optimism for better operational forecasts, notably for the seasonal prediction of high frequency variables and particular events. For the time being, the Nino-3.4 SST and ENSO state for the *Kiremt* season, supplemented by the IOD (for the *Bega* and *Belg* seasons) provide reliable moderate skill at 1 to 2 months lead time for the Ethiopian seasonal climate.

Appendix

Fig. 7.1. Location of SST predictors for *Belg* season, as described by (Diro et al., 2008): (a) Zone I; (b) Zone II; (c) Zone III; (d) Zone IV; and(e) Zone V; (f) homogeneous rainfall zones for the *Belg* season.

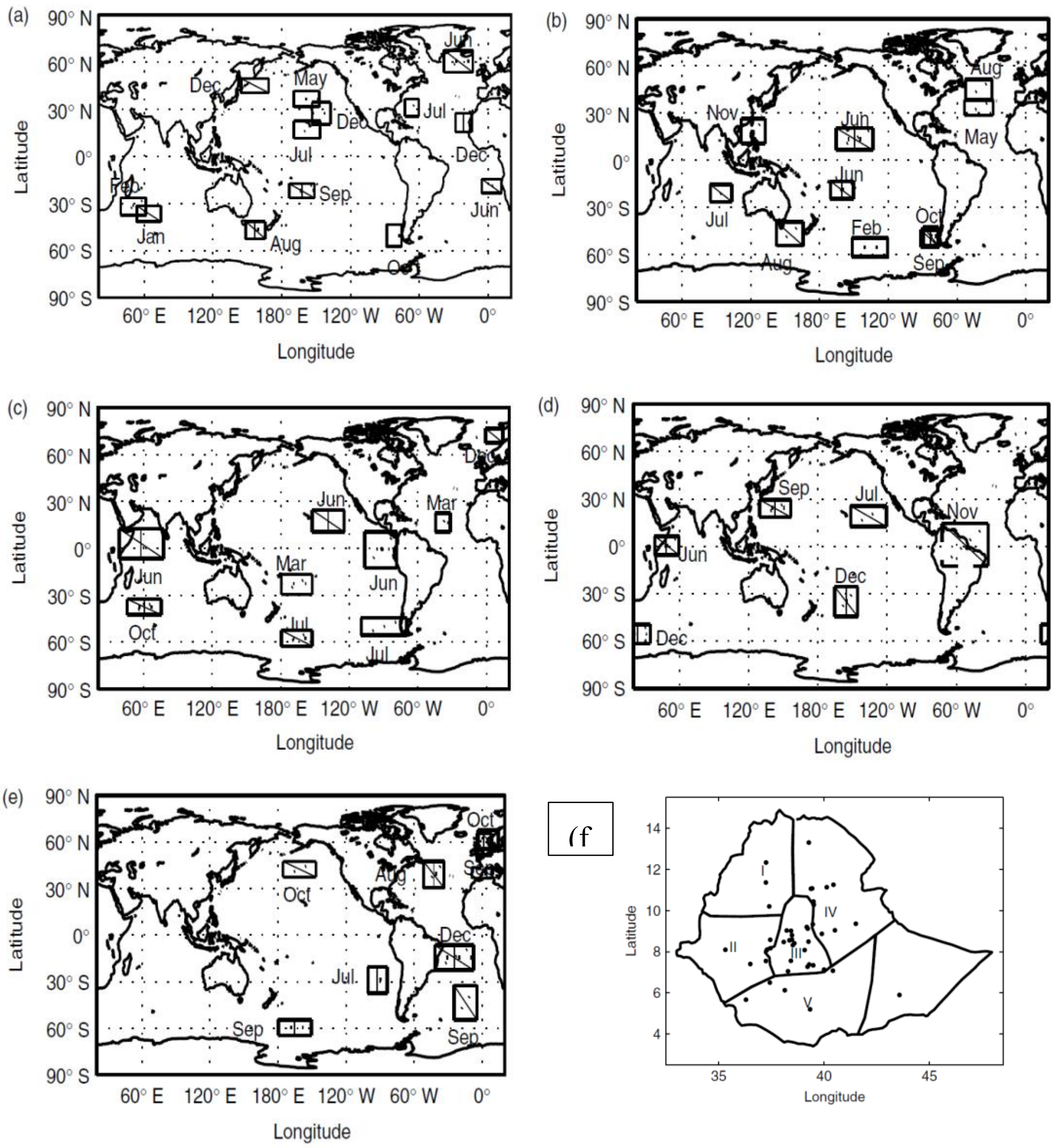

Table 7.1. Location of predictors for JAS (top) and MAM (bottom); as developed by (Nicholson, 2015) for 1-and 2-month lead times.

March			April			May		
ID	Level	Location	ID	Level	Location	ID	Level	Location
1-month lead time								
u_1	850	37°–45°N, 5°W–20°E	u_5	850	10°–15°N, 97°–85°W	u_7	925	12°–20°N, 130°–115°W
u_2	700	20°–12°S, 95°–105°E	u_6	700	30°–15°S, 15°–25°E	u_8	850	7°S–0°, 170°–185°E
u_3	700	35°–25°S, 95°–110°E	v_2	925	30°–40°N, 107°–95°W	v_5	700	7°–15°N, 15°–25°E
u_4	200	5°S–7°N, 115°–90°W	v_3	700	2°S–7°N, 0°–10°E	v_6	700	20°–10°S, 122°–130°E
v_1	200	0°–17°N, 85°–70°W	v_4	200	7°S–2°N, 85°–75°W	v_7	700	15°–5°S, 179°–177°E
Ω_1	925	10°–2°S, 165°–155°W	Ω_2	Sfc	5°–15°N, 70°–60°W	Ω_4	925	45°–37°S, 60°–80°E
			Ω_3	Sfc	22°–35°N, 67°–55°W	Ω_5	850	35°–45°N, 165°–155°W
						Ω_6	200	17°–25°N, 115°–105°W
						SLP_1	Sfc	25°–35°N, 133°–146°E
2-month lead time								
u_9	925	45°–37°S, 145°–130°W	u_{12}	850	45°–32°S, 77°–97°E	u_{13}	850	15°–25°N, 130°–85°W
u_{10}	850	45°–37°S, 90°–75°W	v_{10}	850	15°–45°N, 160°–145°W	u_{14}	850	37°–30°S, 50°–70°E
u_{11}	200	37°–30°S, 155°–170°E	v_{11}	700	5°–15°N, 155°–170°E	u_{15}	200	37°–45°N, 175°–147°W
v_8	925	30°–37°N, 170°E–180°	v_{12}	200	25°–42°N, 85°–70°W	v_{13}	700	45°–35°S, 172°–162°W
v_9	925	35°–20°S, 0°–10°E	Ω_8	500	35°–45°N, 127°–110°W	Ω_{10}	850	22°–30°N, 120°–125°E
Ω_7	500	45°–32°S, 90°–110°E	Ω_9	200	35°–42°N, 80°–90°E	Ω_{11}	500	40°–45°N, 155°–140°W
SLP_2	Sfc	39°–45°N, 150°–172°E	SST_2	Sfc	34°–20°S, 0°–12°E	Ω_{12}	200	25°–12°S, 115°–122°E
SST_1	Sfc	41°–31°S, 176°–186°E	SST_3	Sfc	36°–26°S, 92°–104°E			

March			April			May		
ID	Level	Location	ID	Level	Location	ID	Level	Location
1-month lead time								
u_1	700	7°S–2°N, 25°–37°E	v_3	850	7°–15°N, 52°–62°E	u_7	925	25°–32°N, 42°–22°W
u_2	700	15°–7°S, 152°–167°E	v_4	200	12°–27°N, 12°–27°E	u_8	925	37°–45°N, 170°–150°W
u_3	700	27°–32°N, 150°–170°E	v_5	200	37°–45°N, 75°–95°E	v_6	925	2°S–7°N, 139°–147°E
u_4	200	0°–10°N, 107°–85°W	u_5	200	35°–45°N, 127°–160°E	Ω_2	200	32°–42°N, 110°–100°W
v_1	700	7°–22°N, 147°–130°W	u_6	200	45°–32°S, 155°E–180°	Ω_3	925	2°S–2°N, 0°–10°E
v_2	200	2°S–7°N, 160°–142°W				Ω_4	700	17°–27°N, 77°–62°W
Ω_1	500	10°–5°S, 12°–2°W						
2-month lead time								
SST_1	Sfc	32°–40°N, 10°–30°E	u_9	700	15°–5°S, 50°–5°W	u_{10}	700	5°S–5°N, 20°–37°E
SLP_2	Sfc	20°–7°S, 35°–20°W	v_7	200	30°–40°N, 85°–110°E	SST_2	Sfc	10°–18°N, 186°–195°E
Ω_5	200	7°S–5°N, 80°–60°W	v_8	850	10°S–0°, 20°–40°E	Ω_8	700	15°S–10°N, 35°–40°E
Ω_6	850	40°–32°S, 142°–130°W	Ω_7	700	22°–30°N, 100°–105°E	Ω_9	200	10°–22°N, 42°–30°W
						v_9	200	7°–20°N, 15°–2°W

Table 7.2. Correlation between predictors and summer (*Kiremt*) rainfall regions for 1- and 2-month lead times

1-month lead time						2-month lead time					
March		April		May		March		April		May	
ID	Corr	ID	Corr	ID	Corr	ID	Corr	ID	Corr	ID	Corr
Equatorial rainfall region											
u_1	0.37	u_5	−0.47	u_7	−0.42	u_9	0.34	u_{12}	−0.38	u_{13}	0.40
u_2	0.42	u_6	0.33	u_8	0.32	u_{10}	−0.37	v_{10}	0.62	u_{14}	−0.32
u_3	−0.42	v_2	0.35	v_5	−0.48	u_{11}	−0.42	v_{11}	0.41	u_{15}	−0.35
u_4	0.45	v_3	0.39	v_6	0.35	v_8	0.38	v_{12}	0.44	v_{13}	0.40
v_1	0.38	v_4	0.48	v_7	0.36	v_9	0.41	Ω_8	0.46	Ω_{10}	0.44
Ω_1	0.41	Ω_2	0.48	Ω_4	0.44	Ω_7	0.46	Ω_9	0.41	Ω_{11}	0.39
		Ω_3	0.42	Ω_5	0.50	SLP_2	−0.41	SST_2	−0.51	Ω_{12}	0.43
				Ω_6	0.36	SST_1	0.35	SST_3	−0.44		
				SLP_1	0.39						
Summer rainfall region											
u_1	0.32	v_3	0.40	u_7	0.43	SST_1	−0.36	u_9	0.46	u_{10}	0.48
u_2	0.41	v_4	0.42	u_8	0.41	SLP_2	−0.38	v_7	−0.41	SST_2	0.43
u_3	−0.32	v_5	0.56	v_6	0.45	Ω_5	−0.39	v_8	−0.45	Ω_8	−0.41
u_4	0.50	u_5	−0.41	Ω_2	0.45	Ω_6	−0.45	Ω_7	−0.51	Ω_9	0.44
v_1	0.60	u_6	0.36	Ω_3	0.49					v_9	0.38
v_2	−0.35			Ω_4	−0.42						
Ω_1	0.32										

Table 7.3. February predictors for the *Belg* (MAM) rainfall regions

Sector (°)	Variable	Symbol	Correlation
22 to 37, −22 to −17	u 200 mb	u_1	−0.29
−177 to −142, 12 to 22	SLP	SLP_1	−0.28
−57 to −37, −37 to −35	SLP	SLP_2	0.29
−162 to −137, 40 to 45	SST	SST_1	0.34
32 to 42, −27 to −22	SST	SST_2	0.29

Table 7.4. May predictors for the summer (JAS) rainfall regions

Sector (°)	Variable	Symbol	r
30 to 50, 0 to 10	u 200 mb	u	−0.61
(170 to 265, −5 to 5)–(137 to 160, 18 to 28)	SST diff	SST	−0.71
80 to 90, 5 to 15	SLP	SLP	−0.57

Source: Nicholson (2015)

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