Technical Work Package to Support Enhancements to Seasonal Forecast Production – Final Project Report

Andrew Colman, Tamara Janes, Patricia Nying'uro, Ayub Shaka, Richard Graham, Richard Jones

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Kenya Meteorological Department

Met Office Hadley Centre

Contents

Acronyms **2**

1. Introduction **3**

2. Improved Lead Time for Seasonal Forecast Production **3**

2.1. Development of 'Fixed' Predictors 4

3. Improving Physical Basis for Seasonal Forecasts **8**

3.1 Clustered Forecast Zones 8

3.2 Investigations into Forecasting Rainy Season Onset 15

4. Reliable Methods for the Production of Downscaled Seasonal Forecast Information **21**

4.1 FACT/FIT – Forecast Interpretation Tool 21

5. Summary **26**

6. Plans for Future Work **26**

7. References **29**

Acronyms

NMS	National Meteorological Service
USGS	US Geological Survey
FEWSNET	Famine Early Warning Systems Network
KMD	Kenya Meteorological Department
ENSO	El Nino-Southern Oscillation
GloSEA5	Global Seasonal Forecasting System 5
RCOF	Regional Climate Outlook Forum
GHACOF	Greater Horn of Africa Climate Outlook Forum
GHA	Greater Horn of Africa
MLR	Multiple Linear Regression
MAM	March-April-May
OND	October-November-December
EOF	Empirical Orthogonal Function
NCEP	National Centres for Environmental Prediction
FEWS	Famine Early Warning Systems
ARC2	African Rainfall Climatology Version 2
GPCP	Global Precipitation Climatology Project
TARCAT	TAMSAT African Rainfall Climatology and Timeseries
TAMSAT	Tropical Applications of Meteorology using Satellite Data
ICPAC	IGAD Climate Predication and Applications Centre
CHIRPS	Climate Hazards group InfraRed Precipitation with Station data
PRECIS	Providing Regional Climates for Impacts Studies
CPT	Climate Predictability Tool
CLIMSOFT	CLIMatic SOFTware

1. Introduction

The production of seasonal forecast information is a key activity for East African NMSs such as the Kenya Meteorological Department (KMD). The information produced in seasonal forecast activities is used to inform government bodies, livelihood sectors and the general public on the expected conditions in an upcoming rainy season. It is a key piece of information for informing decision-making activities across Kenya on seasonal timescales, and feeds directly into agricultural practices, food security, water resource management and disaster risk reduction activities.

Within the StARCK+ Ada Consortium, a number of opportunities for seasonal forecast enhancements had been identified through engagement with government stakeholders and local communities. In order to progress towards addressing these user needs, a technical work package was designed and undertaken during the life of the Ada Consortium. Collaboration between KMD and the Met Office has delivered beneficial enhancements to the production of seasonal forecast information, the results of which are highlighted in this report.

Finally, areas of work have been identified as suitable for future collaboration and investigation, which KMD and the Met Office aim to jointly pursue.

2. Improved Lead Time for Seasonal Forecast Production

The dissemination date of seasonal forecast information has long been driven by the availability of observational sea surface temperature (SST) data and the time required to perform statistical regression techniques necessary for seasonal forecast production in advance of each rainy season. This information is often communicated too close to the season onset to be useful in the development of advisories for decision-making practices. A number of steps were taken within the technical work package to streamline the process of production of seasonal forecasts, leading to an improvement in the lead time of seasonal forecast dissemination by up to 3 weeks. This lead time will allow appropriate authorities sufficient time to interpret, downscale and discuss the seasonal forecast with relevant intermediaries and extension officers in order to create relevant seasonal advisories for their region.

2.1. Development of 'Fixed' Predictors

Regional Climate Outlook Forums (RCOFs) were established in 1997 to enable the production of consensus forecasts for high impact wet seasons in Africa and beyond. Kenya is within the Greater Horn of Africa (GHA) region which is covered by the Greater Horn of Africa Climate Outlook Forum (GHACOF) coordinated prior to each rainy season by ICPAC (IGAD Climate Predication and Applications Centre). As input into this process, climate experts from the region produce seasonal forecasts for their respective countries. This is done by using statistical methods in which pre-season climate variables that are significantly correlated to the oncoming season's rainfall are used to predict properties of the forthcoming "wet" season. The statistical tool used at GHACOF is multiple linear regression (MLR). This was adopted by all the NMSs participating in GHACOF including KMD.

The forecast production process for GHACOF and other RCOFs was designed to be simple and use locally available tools and data wherever possible. Historical observed station rainfall data collected by NMSs including KMD are used as predictands. Historical global and regional sea surface temperatures and other climate variables available online (and provided by ICPAC and participating NMSs at GHACOFs) are used as predictors. The forecast production process then involved 'training' the MLR prediction models using these data.

Today, the GHACOF process is 18 years old and fresh forecast models have been designed for Kenya and other GHA countries for each wet season for every year since 1998 using the above procedure. It may now be timely to establish a fixed forecast system which avoids the need to create a new prediction system every year. The purpose of the analysis described here is to create this new, fixed prediction system. A fixed predictors system has been designed based on the predictors used at the last GHACOF for the season of interest. No new predictors have been added, such as using as output from dynamical models, though this may be included in future upgrades. The fixed predictor forecasts continue to use the same pre-season climate data and MLR.

The process currently used to produce seasonal forecasts for GHACOF by KMD and other GHA NMSs is illustrated by the flow diagram in Figure 1. The whole process of collecting and processing the data, finding suitable predictors and creating a forecast can take 2 to 4 weeks.

Most countries that participate in GHACOF generate their forecasts for several climatically homogeneous zones, each normally represented by a single station. Kenya is divided up into the 12 zones shown in Figure 3. Prior to each GHACOF, linear regression models are selected for each zone using stepwise regression to select from a large basket (typically 200) candidate predictors. Predictors are chosen that perform well throughout the historical record (1961 to the preceding year) as shown in the flow chart in Figure 1. Processing time is increased by the need to extract data from various sources and convert into a format suitable for producing a forecast.

The flow chart in Figure 2 illustrates the replacement “fixed predictors” process. The two main changes are (a) use of regression equations and predictors selected well before the forecast is needed and (b) the use of the IRI data library for quicker data retrieval. Forecast equations are stored in excel sheets prepared in advance so at the time of forecast, all that is needed is to retrieve the appropriate indices and substitute into the regression equations stored in excel.

The IRI data library http://iridl.ldeo.columbia.edu/index.html?Set-Language=en enables quick retrieval of real time predictor data in a format which can be easily substituted into the regression equations in excel. The IRI data library uses a language called INGRID, (formerly called expert mode) which can be used to access, reformat and download data required. Below is an example of such a script, which is requesting mean sea surface temperature (SST) anomalies for January 2015 for the region 20S to 10S, 20W to 15 E from the NOAA ERSST version 3b dataset. The anomaly is standardised by dividing by the climate standard deviation of 1.042 C.

```
.NOAA .NCDC .ERSST .version3b .anom
 T (Jan 2015) VALUES
 Y (20S) (10S) RANGEEDGES
 X (20W) (15E) RANGEEDGES
 [X Y]average
```

1.042 div

Scripts like this are used to download all the data required to substitute in to the equations in excel. Such scripts are easily stored in ASCII text files.

A trial “fixed predictor” forecast was produced for MAM 2014 using the same prediction models as used by KMD for the MAM 2013 forecast (Khasandi, Kuya and Nying’uro, 2013). Tercile category forecasts produced by KMD, GHACOF issued forecasts for Kenya and observations are presented in Table 1. The fixed predictor forecasts were 30% correct and the issued forecasts 40% correct. Both therefore were quite close to the chance level of 33%. However, an assessment of one seasonal forecast (for MAM 2014) is insufficient however to provide a statistically robust assessment of the forecast methods used.

Table 1: Evaluation of Experimental Fixed Predictor forecast for MAM 2014. W=Wet, A=Average, D=Dry, AD=average to dry, AW=average to wet.

Zone	Fixed	Issued	Observed
Z2	W	D	D
Z3	AW	AW	A
Z4	W	A	A
Z5	W	AD	W
Z6	A	A	A
Z8	A	W	D
Z9	W	AW	A
Z10	W	A	D
Z11	AD	W	A
Z12	W	W	D

Whilst the predictors and the MLR tool used remains the same, a modification has also been introduced to the forecast process to make the process simpler, quicker and more robust. This is the clustering of predictand zones which is discussed in section 3.1.

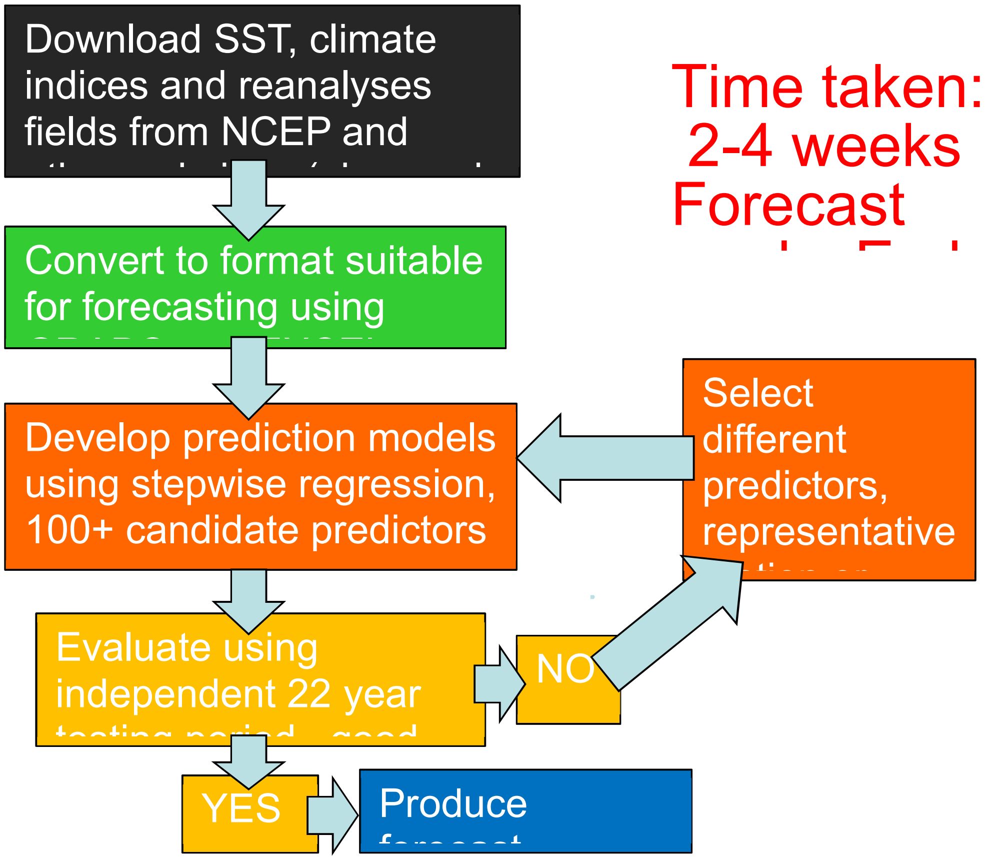

Figure 1: Current GHACOF forecast preparation process.

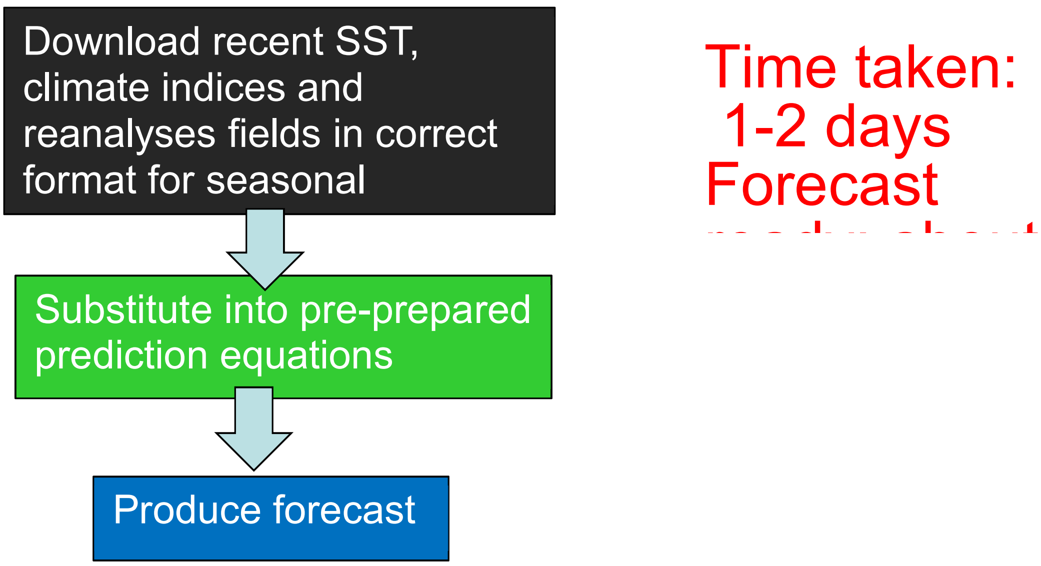

Figure 2: Streamlined forecast preparation process.

3. Improving Physical Basis for Seasonal Forecasts

3.1 Clustered Forecast Zones

A map of the 12 zones for which seasonal rainfall forecasts are produced by KMD for GHACOFs is presented in Figure 3. Currently, the seasonal rainfall in each zone is effectively treated as being completely independent of the rainfall in all the other 11 zones. This assumption of independence is very unlikely to be true. Because of the time scales involved and the spatial scales of teleconnections on which seasonal forecasts are based (eg. ENSO), seasonal signals tend to be on larger scales than just one zone.

In addition, the number of predictors utilised is perhaps large relative to the known drivers of climate variability (e.g. ENSO and Indian Ocean indices). For MAM 2013 ((Khasandi, Kuya and Nying'uro, 2013), a total of 53 different predictors were used to predict the 12 zones, and only 4 of these 53 predictors were common to more than one zone. Given there was a pool of about 150 predictors to choose from, this is consistent with what would be expected if the predictors were being selected by random chance. A large number of predictors – with little commonality across zones is also apparent for the MAM 2014 (Nying'uro et al 2014) and MAM 2015 (Simiyu and Gacheru, 2015) forecasts as well.

In view of the fact that seasonal forecasting is large scale in nature (Cusack and Arribas, 2009), and in order to reduce the number of predictors and the potential for over-fitting, a clustering analysis has been applied to the 12 zones.

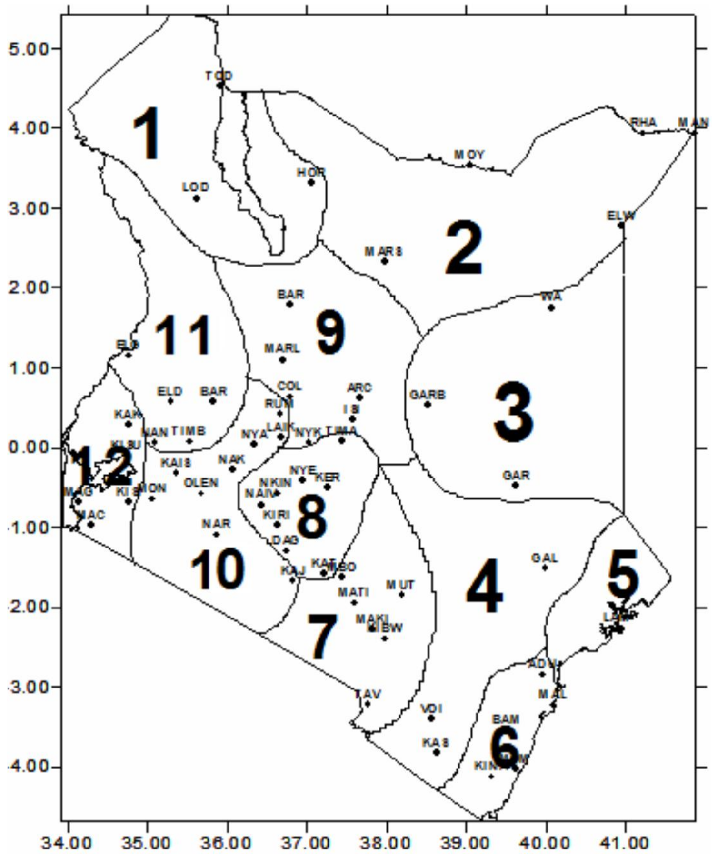

Figure 3a: Homogeneous climatic zones for MAM.

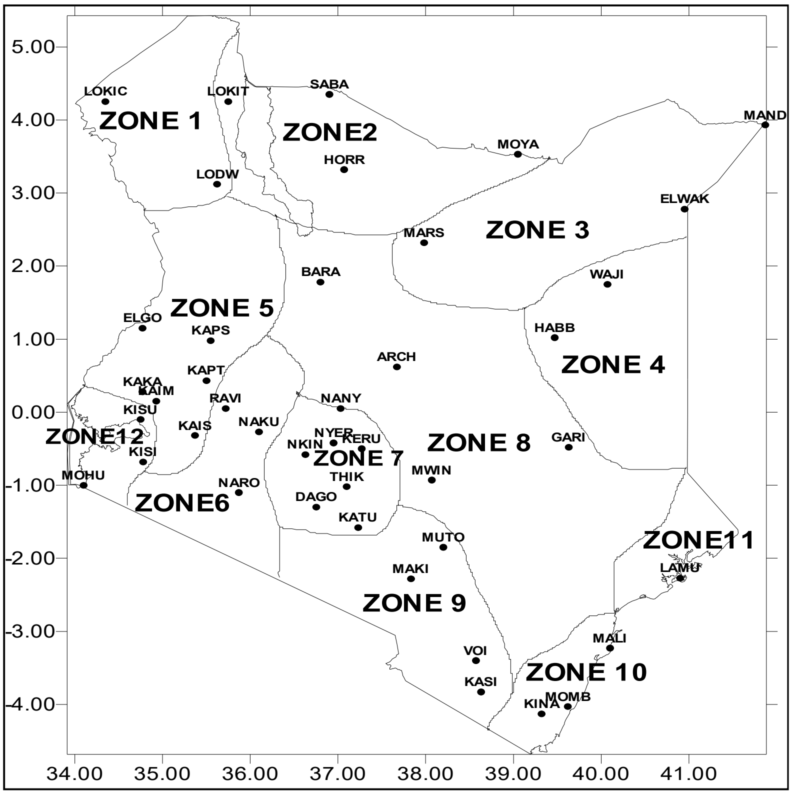

Figure 3: Homogeneous Climatic zones over Kenya for (a) March-April-May (MAM) and (b) October-November-December

The clustering method used is based on a correlation matrix between the historical seasonal rainfall totals for the 12 stations representing the 12 zones in Kenya. Clusters are selected using the following criteria:

(a) Correlation between station series within a cluster is generally high, exceeding a certain threshold.
(b) Correlation between station series in different clusters is low, below a certain threshold
(c) Each cluster contains at least 2 zones if possible
(d) There are no more than 5 clusters
(e) The clusters look physically realistic and coherent (eg zones are together)

Two sets of cluster analyses were carried out for the MAM season and the OND season respectively. Whilst there are 12 zones for each season, the zones for the 2 seasons are different. The distribution of rainfall in the 2 seasons is different (Indeje et. al. 2000) thus separate sets of clusters are needed.

Various objective methods of selecting clusters are available which can be done automatically. For this exercise, a semi-subjective (manual) approach was taken, particularly in view of criterion (e). For MAM, rainfall totals for 12 stations representing the 12 zones were correlated over the period 1972-2013, the longest period with common data available for all 12 stations. Five clusters were found where correlation between station rainfall series within clusters was > 0.36 and correlation between most (90%) station series in different clusters was < 0.36. The five clusters include a large cluster covering central parts of the country (zones 2 Marsabit, 7 Makindu ,8 Dagoretti ,10 Eldoret ,11 Nakuru), a "far west" cluster (zones 1 Lodwar, 12 Kisumu), a "coastal" cluster (zones 5 Lamu, 6 Mombasa), a "lowlands/near coast" region (zones 3 Garissa, 4 Voi) and a small "highlands" cluster consisting of just zone 9 (Nanyuki).

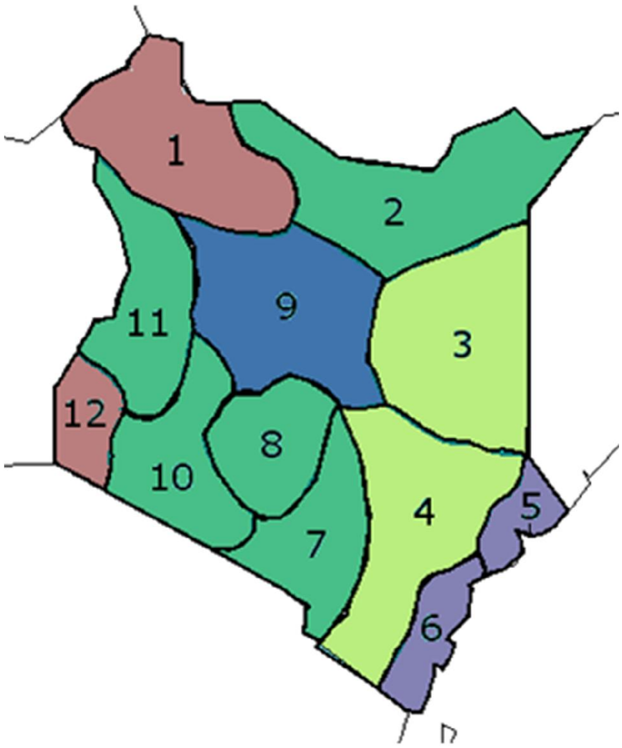

Figure 4: MAM clusters. Coloured shading represents the different clusters.

The clusters are cross checked against other datasets and studies for authenticity. The shape of the largest MAM cluster shows some resemblance to the first Empirical Orthogonal Function, or EOF (a method for identifying principal components), for MAM East African rainfall displayed by Indeje et al. (2000), which has strong weights over the SW quadrant and over central north Kenya. When compared with EOFs of NCEP PREC/L (Chen et. al. 2002) and FEWS ARC2 data (Novella and Thiaw, 2013) for the Kenya region (Figure 5), the patterns appear to be consistent with the clustering, with the EOFs showing some distinction between the far west, middle and coastal regions.

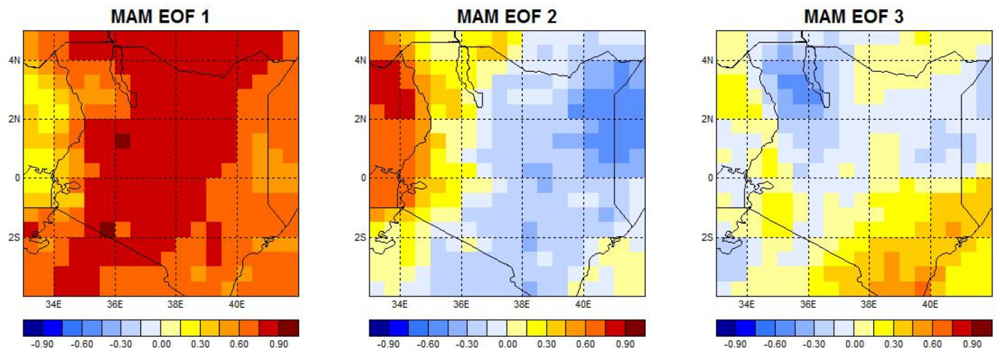

Figure 5: First 3 EOFs of MAM 1981-2010 rainfall over Kenya. Data source is NCEP PREC/L (1981-1982) and FEWS ARC2 (1983-2010).

For OND, data was available for a longer period spanning 1961-2013. Station data for OND is much more highly correlated than for MAM, and 3 clusters were identified using a correlation threshold of 0.6. The three clusters identified were West Kenya (zones 1, 5, 6 and 12), Central & East Kenya (zones 2, 3, 4, 8, 10, 11) and South Kenya Zones (zones 7 & 9).

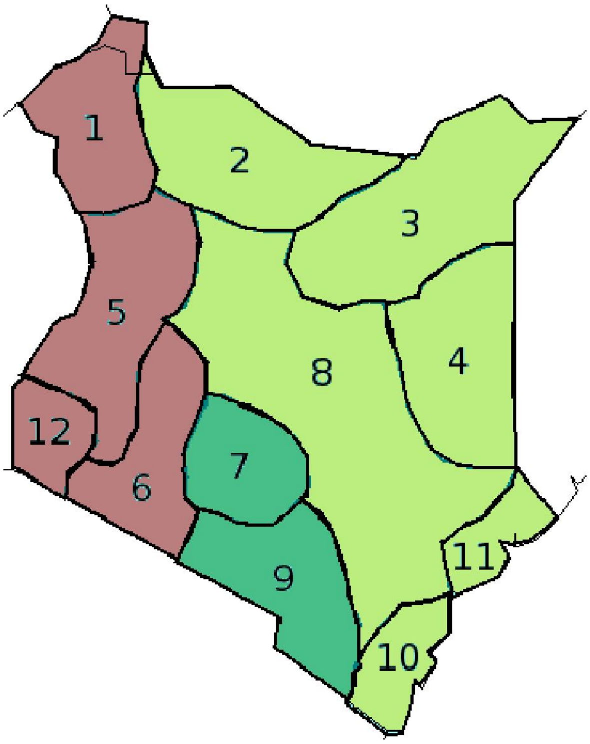

Figure 6: OND clusters.

The EOFs of gridded rainfall for Kenya (Figure 7) show much more coherence over the country as a whole than for MAM, with EOF1 showing similar weights for the whole region. This is consistent with the higher correlation between the zone station time series. EOFs patterns 2 and 3 appear to be consistent with the clustering by showing some distinction between the far west and south eastern regions.

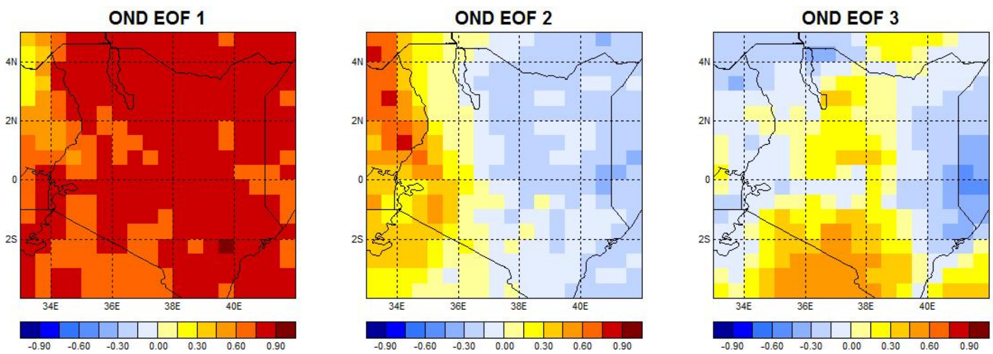

Figure 7: As in Figure 5, but for OND.

Following identification of the clusters, stepwise regression is used to select a set of predictors to predict the mean rainfall for each cluster (average of the stations within the cluster). The candidate predictors are the same as those used for the previous GHACOF, as in the 'fixed predictor' system described previously. The difference is that just 5 sets of predictors are selected for the 5 MAM clusters rather than 12 sets for the 12 zones respectively. The result is one equation for each cluster rather than one per zone. These equations are used to predict all the zones in that cluster, therefore all the zones within a particular cluster will have the same forecast.

The preparation of the cluster regression equations can be done at any time prior to the forecast and is not dependent on the availability of data to substitute into the equations to make a forecast. The performance of forecasts for MAM rainfall using the clusters is compared with the performance of the current method used for GHACOFs where separate models are used to predict each zone and also with the performance of issued forecasts (Table 2). The cluster and zone forecasts are both evaluated using stepwise regression models calculated over the training period 1971-2004. The skill of issued forecasts is also provided for reference but note that these cannot be compared directly with the cluster and zone forecasts as they use different training periods which may have extended to more recent years for the later forecasts (e.g. perhaps 1971-2013 to predict 2014) and may include subjective modifications from forecaster interventions.

Skill is highly variable between zones and is on average quite low for all methods shown here. The issued forecasts perform better than the other 2 methods by a small margin, but there is substantial negative skill for 4 zones. The cluster forecasts do slightly outperform the equivalent zone forecasts, suggesting that the clustering does not harm skill at least.

Table 2: Correlation skill of predictions for MAM 2005-2014

2005-2014	Issued	Cluster (71-04)	Zone (71-04)
Z1	-0.4949	-0.5663	0.0522
Z2	0.0230	0.4359	-0.2096
Z5	0.1751	-0.0063	0.3324
Z6	0.1277	-0.2660	-0.1365
Z7	-0.0077	-0.1223	-0.5676

Z8	0.2918	0.3240	0.0876
Z9	0.3450	0.6121	0.6121
Z11	0.4859	0.3841	0.1254
Z12	-0.2344	-0.1662	0.3219
Z10	0.1687	0.4322	-0.3076
Z3	0.8483	-0.2779	0.1357
Z4	-0.2179	0.0961	-0.0093
AVERAGE	0.1259	0.0733	0.0364

Producing a seasonal forecast on these clustered zones substantially reduces the time and effort needed prior to each season, as the number of regression models to be run is fewer. The forecasts are arguably more physically robust than before and there is no apparent loss of skill.

3.2 Investigations into Forecasting Rainy Season Onset

Currently, the prediction of rainy season onset and cessation is performed using a complex, subjective method known as the ‘analogue method’. Through visually comparing recent sea surface temperature patterns in the Pacific Ocean (specifically within the ENSO region) to sea surface temperature patterns in previous years, a year (or multiple years) with similar patterns is identified as an ‘analogue year’, which is used to predict the onset and cessation of an upcoming rainy season. It will be assumed that the observed rainy season start and end dates within the analogue year will be similar to what will be experienced in the upcoming season. The choice of analogue years is a highly subjective process, and this may contribute to errors in resulting forecasts of onset timing.

Within this project, preliminary comparisons were performed between the above ‘analogue method’ and dynamical forecasting methods currently in use at the Met Office (i.e. GloSea5). Through investigating seasonal hindcast output from GloSea 5, spanning 1996-2009, and following the ‘local’ definition of rainy season onset as defined in Vellinga *et al.* (2013), where the start of a rainy season occurs when 20% of the seasonal total rainfall has been accumulated at a point, predicted (GloSea5 and analogue) and observed rainy season onset dates could be determined for all parts of Kenya. The same method was then applied to two observational datasets (GPCP – Global Precipitation Climatology Project, and TARCAT – TAMSAT African Rainfall Climatology and Timeseries) for the analogue year previously identified by KMD for the season in question (with thanks to Mr. James Muhindi from KMD for compiling this information). Both 'predicted' rainfall onset dates were then compared to observed onset dates, to assess any benefits or drawbacks of both forecasting methods.

Previous forecast information was available from 2000 onwards, with analogue years available for the MAM and OND seasons (see Table 3). In addition to this, because some of the analogue years identified are quite far into the past (i.e. 1965 as the analogue year for MAM 2004), it was difficult to perform any analysis due to a lack of observational datasets for these years. It was therefore only possible to perform preliminary analysis on 6 of the 10 years in Table 3 (these are highlighted within the table).

Table 3: Analogue Years for KMD Forecast (observational data available for highlighted years only)

Year	Season	Analogue Year
2000	MAM	1976
	OND	1983
2001	MAM	1984
	OND	1984
2002	MAM	1997
	OND	1968
2003	MAM	1995
	OND	1990
2004	MAM	1965
	OND	1994
2005	MAM	1970
	OND	1974
2006	MAM	1975
	OND	1977
2007	MAM	1987

	OND	1995
2008	MAM	1999
	OND	1964
2009	MAM	1972
	OND	2002

Three years from this analysis have been selected for further discussion in Figures 8-10. These figures depict the calculated rainy season onset date in pentads (meaning 5-day periods starting from October 1st), for the two observational datasets, the dynamical seasonal forecasting method and the ‘analogue year’ method. For 2001, it can be seen that the calculated start of the rainy season was in early October for western parts of Kenya, moving eastward towards the coast as the season progresses, with relative consistency between the ‘analogue’ and GLOSEA methods (Figure 8). The stark contrast in resolution and observed values between the two observational datasets can be clearly seen here, and remains a key obstacle to forecast validation in this region. While GPCP contains a combination of rain gauge station data, sounding observations and satellite information, TARCAT contains considerably higher-resolution data due to relying solely on satellite information. Furthermore, the resolution of the GLOSEA dynamical seasonal forecast product is quite coarse, making it difficult to capture local influences on seasonal climate. For 2004, it can be argued that the GLOSEA method does a reasonably better job at capturing the later rainy season onset experienced in Northern Kenya, while both methods seem to capture early rains in coastal regions (Figure 9). In 2007, both methods seem consistent again with observations, with the GLOSEA method performing slightly better over the wetter western regions of Kenya (Figure 10).

Given that analogue years are chosen based on observed SST patterns in the tropical Pacific, and have been shown here to provide reasonably consistent information with observations over a select number of years, it would be useful to define an objective method for identifying analogue years, collaboratively with KMD. This would allow for a quicker production of the seasonal forecast, with potentially more robust information on rainy season onset dates. Additionally, information from dynamical seasonal forecasts could provide an alternative or supplementary source of input if this information can be included in the seasonal forecast production process. Before this can happen, further co-produced analysis following on from the above results will be required.

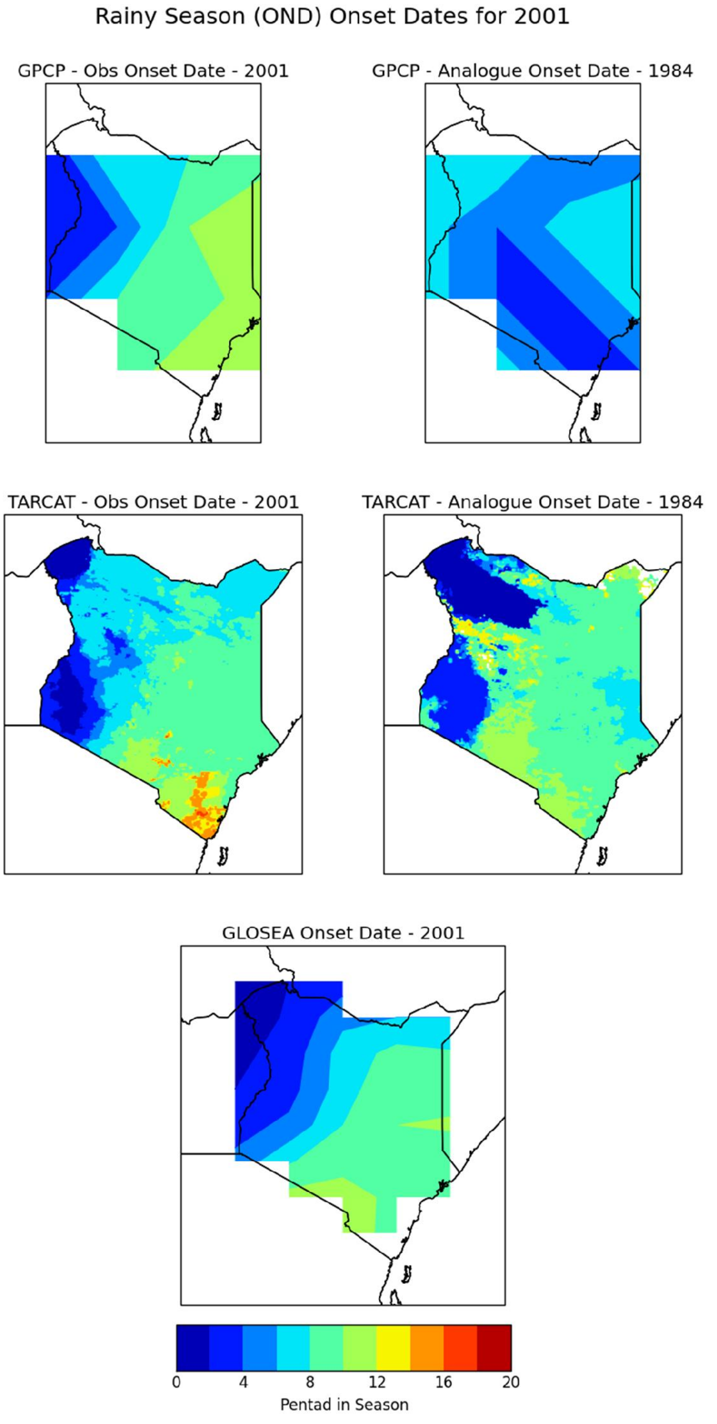

Figure 8: Rainy season onset dates (in pentads) for 2001, comparing observed and forecast onset dates using two different forecasting methods ('analogue year' method and dynamical seasonal forecasting).

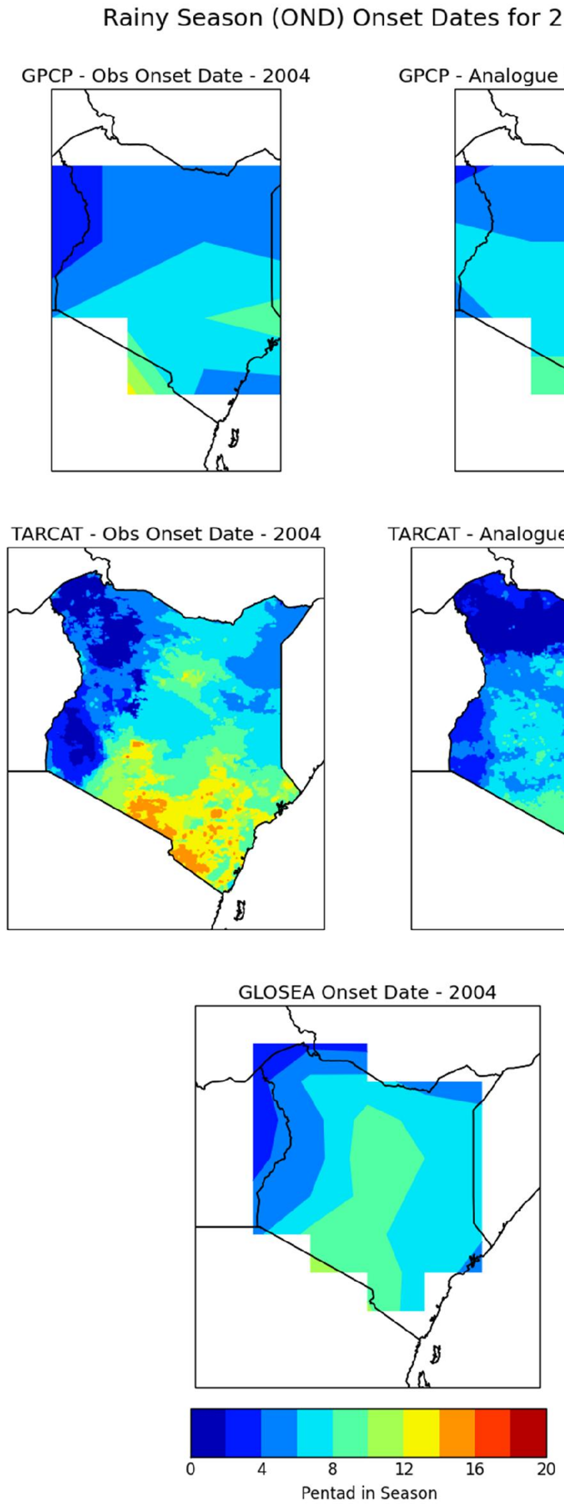

Figure 9: As in Figure 8, but for 2004.

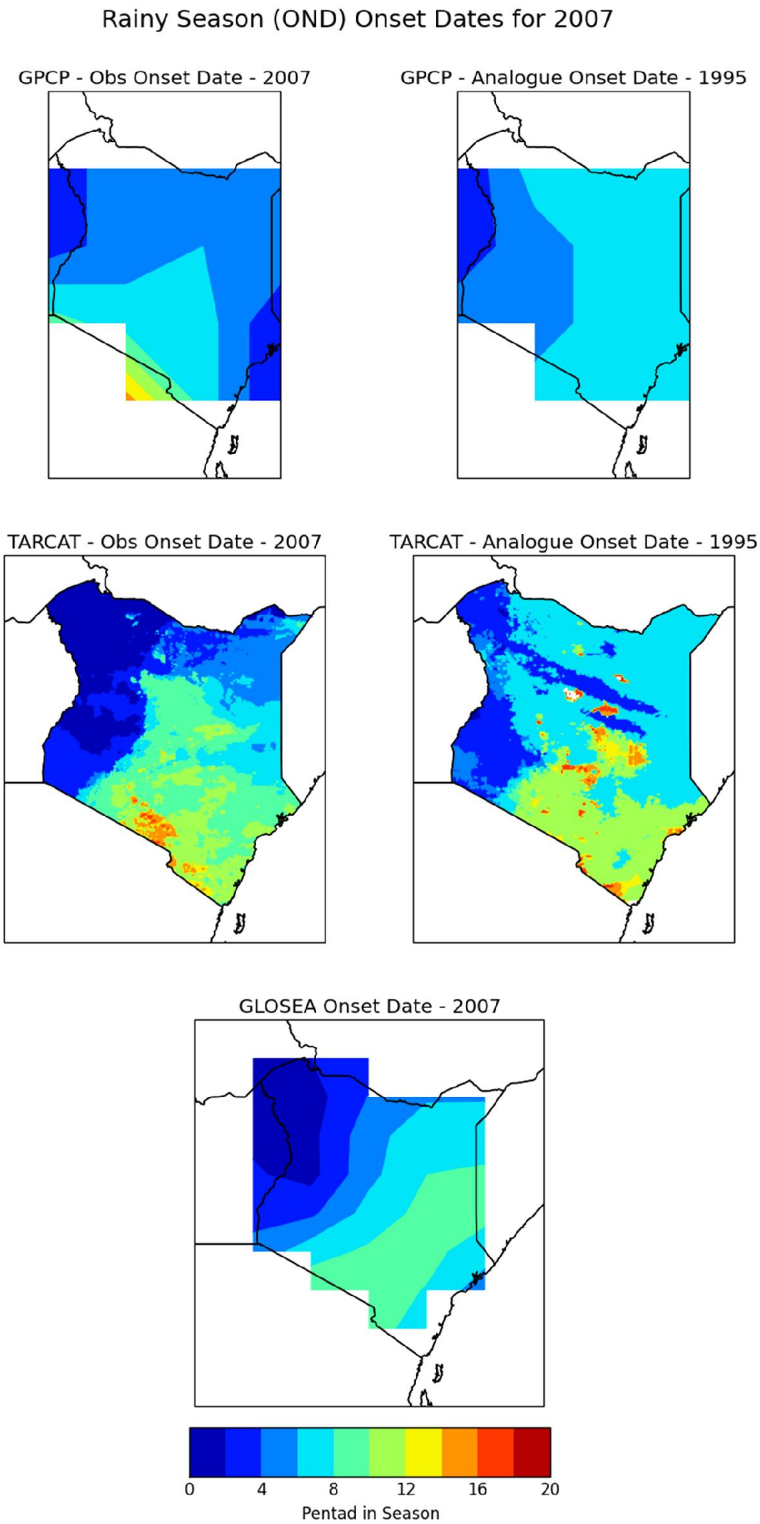

Figure 10: As in Figure 8, but for 2007.

4. Reliable Methods for the Production of Downscaled Seasonal Forecast Information

Seasonal forecast information is often produced on scales too large to inform local decision making practices. Through engagement with local government and communities in Kenya, a need for higher-resolution seasonal forecast information and improved dissemination techniques was identified in order to ensure the use of this information in key decision-making activities throughout a season. This section outlines an interpretation tool which was trialled in 5 focal counties in Kenya (Isiolo, Makueni, Garissa, Wajir, and Kitui), and subsequently upscaled for use in all 47 counties in the country.

4.1 FACT/FIT – Forecast Interpretation Tool

The FEWS Agro-Climatological Tool/Forecast Interpretation Tool, also known as FACT/FIT, was collaboratively designed by USGS and FEWSNET. This tool provides the capability to downscale tercile-based seasonal forecast information, such as that produced by KMD and other NMSs across East Africa, to produce higher-resolution forecast information and probabilities of threshold exceedance.

The FIT component of this tool kit relies on a Monte Carlo resampling of the climatologically derived probability distribution for rainfall in proportion to forecast probabilities for an upcoming month or season (Husak et al., 2011). Through estimating new distribution parameters defining the probability distribution for the forecast interval, the FIT tool can be used in assessing the likelihood of specific events during the forecast time period for a specific station or region. The technique requires a reasonable climatological rainfall distribution for the same time interval as the probabilistic forecast, and assumes a gamma distribution as a best fit (shown to perform well over 97% of the African continent, Husak et al., 2007; Husak, 2005). The output of FIT is a new set of probability distribution parameters that represent the chosen forecast probabilities. Assessments of the FIT tool's performance in Husak et al. (2011) suggest a good representation of forecasts, with typical maximum errors on the order of 2-3%, which may be within the uncertainty range of the 30+ observations needed to create the initial climatological distribution.

The FACT component of the FACT/FIT tool kit utilizes the FIT algorithm to translate probabilistic rainfall forecast into potential rainfall amounts and anomalies based on the Collaborative Historical African Rainfall Model (CHARM) dataset. The CHARM rainfall dataset is produced using three sources of rainfall information: climatologically aided interpolated (CAI) rainfall grids from monthly rain gauge data, daily NCEP/NCAR reanalysis products, and estimates of rainfall enhancement due to complex topography (Funk et al., 2003). By using reanalysis to 'fill the gaps' between interpolated monthly gauge data, the resulting CHARM dataset contains nearly 40 years of daily gridded rainfall information across the African continent with a 0.1° resolution. The FACT toolkit, in conjunction with the CHARM dataset, allows users to generate probability maps indicating locations that are likely or unlikely to receive critical rainfall threshold amounts conducive to agricultural and livelihood activities such as crop production.

The ability to translate probabilistic forecast information into maps of rainfall likelihoods helps both forecasters and users to better understand the potential implications of a forecast on a given region. The FACT/FIT tool was identified as a suitable option for downscaling seasonal forecast information produced by KMD, through a comprehensive review of available products such as PRECIS (Providing Regional Climates for Impacts Studies), CPT (Climate Predictability Tool) and CLIMSOFT (CLIMatic SOFTware). Training on the use of the tool was provided to KMD County Directors from the 5 project counties, and on-going support was provided through online collaboration over Huddle. Due to the successful uptake of this tool across the 5 project counties, training activities were extended to include all 47 KMD County Directors, with a number of the original 5 members of KMD staff becoming 'FACT/FIT Champions' and points of contact within the organisation.

Trial downscaling activities were performed for a number of rainy seasons, for which a selection of results is shown below. For OND 2014, the KMD forecast suggested average to wet conditions across much of western, eastern and coastal Kenya, with a small strip of average to dry conditions contained in Zones 1, 2, 6 and 9 (Figure 11).

These results are quite coarse in resolution, and are therefore difficult to use in local decision-making contexts.

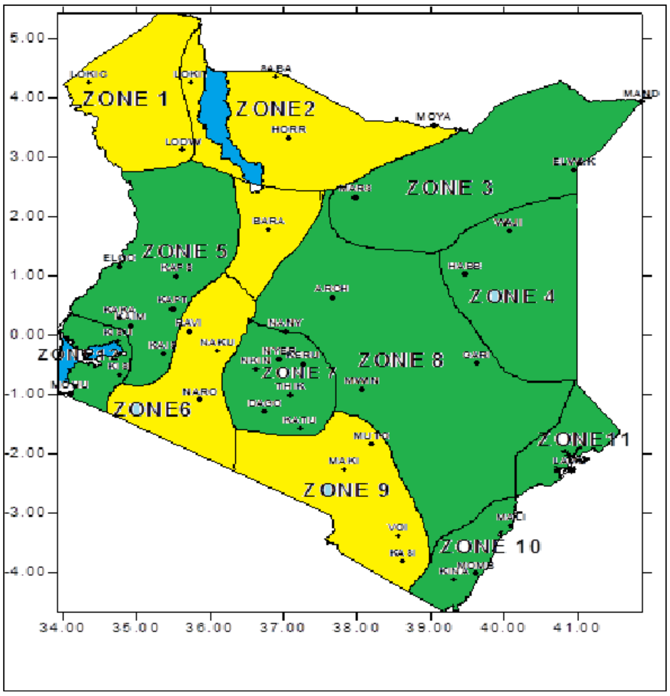

Figure 11: KMD Forecast for OND 2014 (from Nying'uro and Simiyui, 2014). Green zones represent average to wet conditions, and yellow zones represent average to dry conditions.

In order to provide more detailed forecast information, the above forecast was used as input to the FACT/FIT tool, which was used to produce plots on the probability of receiving less than 300mm during the rainy season (Figure 12). The threshold of 300 mm was identified through community engagement activities as the required amount of rainfall for the growth of maize. As can be seen in Figure 13, the information produced by FACT/FIT is at much higher resolution, and will enable better informed decision-making at the county and community level.

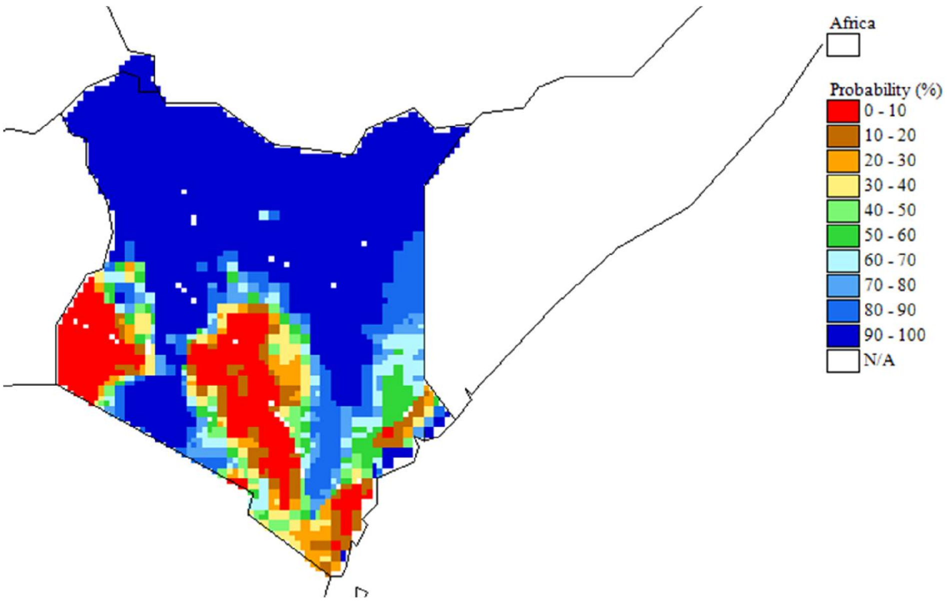

Figure 12: Probability of receiving less than 300mm of rainfall for Kenya, based on the KMS OND2014 forecast.

More recently, a similar trial was performed for the MAM 2015 season. Figure 13 depicts the KMD forecast, which suggests average to wet conditions in much of western Kenya and small portions of the coastal region, with average conditions in central Kenya and average to drier conditions across the remainder of the country. When input into FACT/FIT, the probability of receiving less than 300mm of rainfall is depicted in Figure 14.

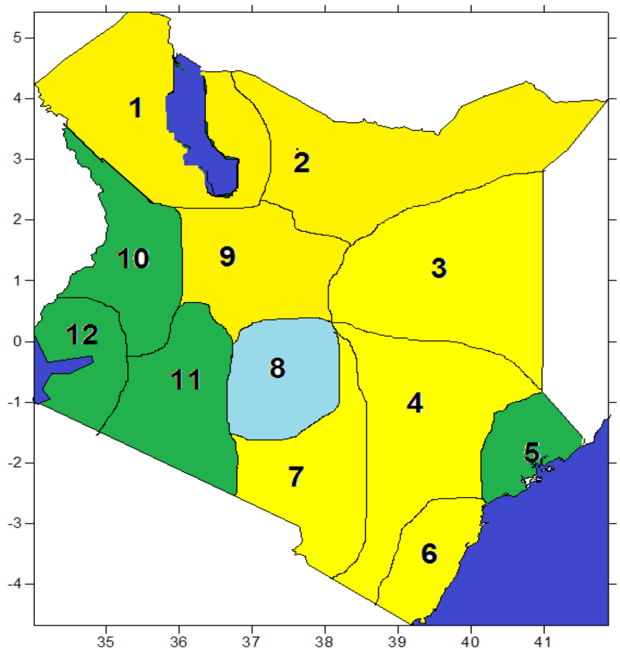

Figure 13: KMD forecast for MAM 2015 (from Simiyu and Gacheru, 2015).

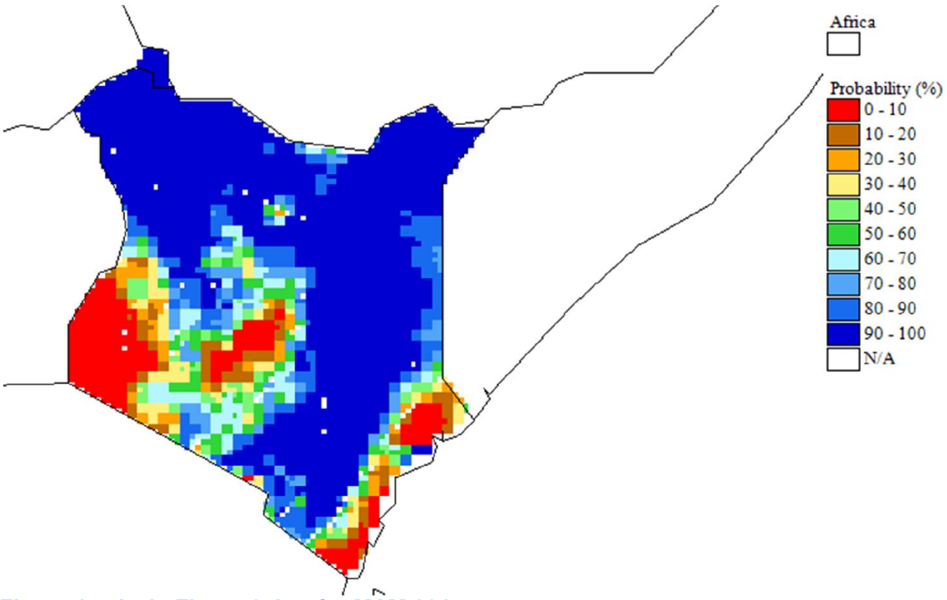

Figure 14: As in Figure 9, but for MAM 2015.

The use of FACT/FIT across a number of counties in Kenya has enabled improved forecast dissemination at local levels, through enhancing the relevance of seasonal forecast information produced at KMD headquarters. Through producing downscaled images for all of Kenya, KMS County Directors of Meteorological Services (CDMs) can extract information from these maps for their respective counties, and provide useful input to decision-making in their local government and communities.

5. Summary

Through the StARCK+ Ada Consortium project, KMD and the Met Office have developed a collaborative scientific relationship, and have successfully investigated potential changes to seasonal forecast production in order to benefit end-users in Kenyan government and local communities.

By streamlining the seasonal forecast production process, we have been able to demonstrate an increased lead time of approximately 3 weeks. Furthermore, through small modifications to the forecast methods, including the clustering of some of the 12 seasonal forecast zones currently in use by KMD and strategically selecting and fixing seasonal forecast predictors, we have identified potential improvement to the physical basis of seasonal forecast production in Kenya. The requirement of higher-resolution forecast information has been identified through a number of user-engagement activities, which we subsequently investigated through the inclusion of dynamical seasonal forecast information, and the use of a computational tool for translating tercile-based seasonal forecast information into probabilities of exceedance at the local, community-based level. This tool has subsequently been used by a number of KMD County Directors of Meteorological Services, in their production of county-based seasonal forecast advisories benefitting local government, intermediaries and community members alike.

6. Plans for Future Work

The achievements of the technical work package summarized above have strengthened the collaborative relationship between KMD and the Met Office, while also highlighting areas where future collaboration will benefit users of forecast information in East Africa.

Areas for future collaboration, some of which have been included in a concept note for the DfID WISER Programme Inception Phase, are briefly described below.

1) Parallel forecast verification

In order to promote the use of new forecast methodologies (described in sections 2.1 and 3.1) as operational, both of the proposed modifications described above require verification across a number of subsequent seasons, to ensure that there is no loss in 'skill' of the seasonal forecast information. The skill of the pilot forecast will be assessed using standard forecast verification metrics, and will be jointly undertaken by the Met Office and KMD. Work will also be undertaken to assess the potential usefulness and general demand for a longer-lead seasonal forecast, building on the community engagement work completed in the Ada Consortium project.

2) Extend pilot forecast to other seasons/timescales

In addition to the forecast verification work described above, the pilot forecast methodology will be extended to encompass other seasons/timescales which haven't currently been investigated. The primary focus of our work in the Ada Consortium has been on the short and long rainy seasons, however the forecast methodology can easily be extended to the June-July-August rainy season and the monthly forecast updates (which are produced in a very similar way to the seasonal forecast). These pilot forecasts would also be verified in a similar manner to what is being proposed in Activity 1) above. Methods for effective communication and potential usefulness of these shorter-range forecasts will also be assessed, to ensure user-needs are being met in an appropriate and realistic manner.

3) Continued research into rainy season onset/cessation

The preliminary assessment of the methodologies for forecasting rainy season onset and cessation (described in section 3.2) highlighted potential relevancy and skill in both the 'analogue' method currently being used at KMD, as well as the dynamical forecast method being implemented at many international seasonal forecasting centres (including the Met Office). This has highlighted the need to do a further assessment of these methodologies, with the aims of achieving the following outcomes:

a. Objective definition of analogue years – this would involve looking at various criteria for defining an analogue year, preferable based on objective methods rather than the current 'by eye' methods that are in practice
b. Robust comparison with dynamical forecasts – while the analysis performed in the Ada Consortium was very preliminary, an extension of this analysis to involve a more robust comparison of dynamical seasonal

forecast output and analogue methods for rainy season onset/cessation would further highlight any accuracy and skill in either method

4) Criteria for operational acceptance

From a more organisational perspective, it will be useful to determine what the existing criteria are for operational acceptance of a forecast product, and how we might be able to operationalise the pilot forecast methodologies described above should they show both a) a decrease in the amount of effort required for forecast production and b) similar or increased level of skill and accuracy to current methods. This will involve an assessment of current organisational practices at KMD, and how these might be improved to accommodate the production and effective communication of new forecast products.

5) FACT/FIT enhancements

In order to further improve on the use of FACT/FIT as a forecast interpretation tool (described in section 4.1), we would propose enhancements to the tool, including up-to-date observational information and access to tercile-based forecast data, in collaboration with the tool's designers at FEWSNET in Nairobi, Kenya. An improved version of CHIRPS, (CHIRPS2.0) has already been developed through the GeoClim project, (http://chg.geog.ucsb.edu/tools/geoclim/), which provides improved data coverage making full use of NMS station observations, not available for CHIRPS1.

6) Gridded seasonal forecasts

Further into the future, it may be the case that gridded seasonal forecast products become high in demand, which is a capability that currently doesn't exist within KMS. There are a number of methodologies currently in use to produce gridded seasonal forecasts, the knowledge of which could be transferred to KMD scientists and forecasters through various capability building activities.

7) Scientific exchanges

Underpinning much of what has been proposed above, scientific exchanges (both to KMD headquarters, KMD county offices and to the Met Office) would be crucial to facilitating a step-change in the current rate of knowledge transfer seen within the Ada

Consortium lifetime. This would allow KMD scientists to familiarize themselves with dynamical seasonal forecast, gridded products and analysis techniques, while also allowing Met Office scientists to better understand the driving needs of end-users of KMD forecast products. Co-generated research on forecast evaluation techniques, such as the robustness of the cluster methodology described in this report during El Nino and La Nina years, would be undertaken during these exchanges.

7. References

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Met Office
FitzRoy Road, Exeter
Devon EX1 3PB
United Kingdom

Tel (UK): 0870 900 0100 (Int) : +44 1392 885680
Fax (UK): 0870 900 5050 (Int) :+44 1392 885681
enquiries@metoffice.gov.uk
www.metoffice.gov.uk