



Seasonal predictability of onset and cessation of the east African rains

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ABSTRACT

Advanced warning of delayed onset or early cessation of the rainy seasons would be extremely valuable information for farmers in east Africa and is a common request from regional stakeholders. Such warnings are beginning to be provided, however forecast skill for these metrics has not been demonstrated. Here the forecast skill of the ECMWF seasonal hindcasts is evaluated for onset and cessation forecasts over east Africa. Correlations of forecasted and observed onset and cessation anomalies are only above a 95% statistical significance level for a small part of the domain during the long rains, whilst they are significant for short rains onset and cessation over a large part of the region. The added value of updating the forecast outlook with the extended range 46 day forecast is assessed and this gives a small improvement. For the short rains detection of early onset is better near the coast, and late onset detection is better over northwestern Kenya.

During exceptionally dry years the method to detect onset and cessation fails. Using this as a definition of a failed season, the model shows significant skill at anticipating long rains season failure in the northwest of Kenya, and short rains failure in Somalia and northeast Kenya.

In addition the strength of the correlation between long rains cessation and seasonal total is shown to be particularly weak in observations but too strong in the hindcasts. Predictability of onset and cessation for both seasons appears to arise primarily from the link with seasonal total and it is unclear that the model represents variability in onset and cessation beyond this. This has important implications for operational forecasting: any forecast of season timing which is 'inconsistent' with seasonal total (e.g. an early onset but low total rainfall) must be treated with caution.

Finally links with zonal winds are investigated. Late onset is correlated with easterly (westerly) anomalies during the long (short) rains, though the strength and spatial pattern of the relationship is not well represented in the model. Early cessation is correlated with easterly anomalies in both seasons for most of the region in both observations and hindcasts. However for the long rains the sign of the correlation is reversed along the coast in observations but not in the hindcasts. These dynamical inconsistencies may have a negative impact on forecast skill and have the potential to inform process-based development of climate modelling in the region.

1. Introduction

The population of largely semi-arid East Africa is exposed to climate variability and although climate change impacts are uncertain (Rowell et al., 2015), risks can be partially mitigated with shorter term forecasts (Washington et al., 2006). Variability in timing of the rains has a significant impact on agriculture and early warning of onset and cessation is a regular request from user needs assessments in the region [e.g. (Owusu et al., 2017)], as it would allow farmers to better manage potential risks to their planting and harvesting activity. To this end, the IGAD Climate Predictions and Applications Centre has started to disseminate onset and cessation forecasts at the Greater Horn of Africa Regional Climate Outlook Forum (GHACOF), though no evaluation of expected skill is provided.

Over east Africa, onset and cessation have generally received less attention from the scientific community than have seasonal totals [e.g. (Nicholson, 2017a)]. Mean dates and variability of the start and end of the rains over Kenya/Tanzania has been determined for the two rainfall seasons (the March–May long rains, MAM, and October–December short rains, OND) (Camberlin and Okoola, 2003; Camberlin et al., 2009; Philippon et al., 2015). For this location it has been demonstrated that

both onset and cessation are well correlated with seasonal total and correlated with each other during the short rains but not the long (Camberlin and Okoola, 2003; Philippon et al., 2015). Long rains cessation has been linked to Indian monsoon onset (Camberlin et al., 2010) and long rains onset here is linked to zonal winds, with anomalous easterlies (westerlies) leading to late (early) onset and an overall dry (wet) season (Okoola, 1999; Camberlin and Okoola, 2003). Though the skill of onset forecasts has been evaluated for west Africa (Vellinga et al., 2013) and it has been demonstrated using an atmospheric model forced by sea surface temperature (SST) that onset of the short rains is more reproducible than the long rains (Philippon et al., 2015), the level of forecast skill for east Africa has not been described in the scientific literature.

Here, the ability of the operational ECMWF seasonal forecast model to anticipate anomalous onset and cessation is determined. Forecasts issued roughly a month ahead of the season are considered, corresponding approximately to the lead time of the forecasts available at the time of the GHACOF. The added value of incorporating the ECMWF extended-range 46-day forecast (benefiting from increased spatial resolution and more frequent updates) is also assessed. The relationships of onset and cessation with both seasonal totals and zonal winds are

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also evaluated, extending the findings of (Camberlin and Okoola, 2003) from over Kenya and Tanzania to the whole of East Africa. Description of the forecasts, observational data and the method used to define onset and cessation are contained in the next section. Results and conclusions follow.

2. Methodology

2.1. Models, experiments and observations

The seasonal forecast system of ECMWF is an initialised dynamical simulation of the coupled atmosphere-ocean climate system and has recently been upgraded to System 5 (hereafter S5). The atmospheric model used is the integrated forecast system (IFS) CY43R1 at Tco319 spatial resolution (roughly 35km near the equator), with 91 levels in the vertical. IFS is coupled to the Nucleus for European Modelling of the Ocean (NEMO) ocean model v3.4 at 0.25° resolution with 75 vertical levels. Compared to the system it replaces, S5 uses newer versions of IFS and NEMO at higher resolution and introduces an interactive sea-ice model, LIM2.

Operationally S5 is initialised once per month. Skill is assessed using the hindcast: 25 member ensembles initialised on the first of every month 1981–2016, with each member starting from slightly perturbed initial conditions in order to sample the uncertainty in knowledge of the exact state of the atmosphere (see (Leutbecher et al., 2017) for details). The atmosphere, land surface and ocean are initialised with ERA-Interim (Dee et al., 2011), ERA-Interim land (Balsamo et al., 2015) and ORA-S5 [an updated version ORA-S4, described in (Balmaseda et al., 2013)]. Model uncertainty is represented with stochastic perturbation schemes (Leutbecher et al., 2017). Here the first five months of the S5 hindcasts initialised on 1st February and September are used to assess the skill of onset and cessation forecasts for the two seasons, approximately equivalent to those available at the start of the GHACOF.

In addition to assessing the skill of the operational seasonal model, the added value of the shorter-range subseasonal system is also considered. A lot of attention has been given recently to the subseasonal (10–40 day) timescale [e.g. (White et al., 2017; Vitart et al., 2017)], though ECMWF has issued a forecast at this timescale for many years. The ECMWF 46 day extended-range forecasts (hereafter ER) are combined here with S5 to assess the benefit of incorporating this information.

There are three potential benefits to ER compared with the first 46 days of the seasonal system. Firstly, ER tracks IFS cycle upgrades, whilst the cycle of the seasonal system is only updated infrequently. In the hindcasts used here however, there is no difference between the ER and S5 model version due to the recent upgrade, though over time the ER cycle will leave S5 behind, until the next seasonal system upgrade.

A second difference is the higher spatial resolution for the first 15 days in ER. To estimate the added benefit of this, the ER hindcasts issued on the first of February and September are combined with S5 by simply replacing the first 46 days of the S5 hindcast with ER data (experiment S5+ER).

Finally, the start dates of ER are more frequent, twice per week instead of once per month. To assess the potential value of an updated forecast, the ER forecasts issued on the 15th of February and September are combined with S5 (S5+ER+14d). Mimicking an operational context in which the accumulated rainfall from 1 to 14th is known by the time of the forecast initialised on the 15th; in the S5+ER+14d experiment days 1–14 are daily observations scaled by the ratio of the long term mean of S5 with observations. Days 15–61 are then replaced with the ER forecast issued on the 15th. As they are run more frequently, computing constraints limit the size of the ER hindcast to 20 years (here the 1996–2015 hindcast is used) and 11 members. When compared with S5+ER and S5+ER+14d, the S5 hindcast is limited to the same period and only the first 11 ensemble members are used. That this combined forecasts may improve on S5 alone if the ER simulation

diverges from S5 and the skill of the ER forecast in the first 46 days is better than that in the equivalent S5 period.

The Climate Hazards group Infrared Precipitation with Stations (CHIRPS) dataset (Funk et al., 2015) is used for verification and to fill in the first 14 days of the S5+ER+14d hindcast. This is a blend of station and satellite information, providing daily precipitation estimates at 0.05° spatial resolution from 1981 to the present. CHIRPS and all model hindcasts are interpolated to a 1° grid before analysis.

2.2. Defining onset and cessation

Many methods exist to determine rainy season onset and cessation dates; at least 18 have been applied to west Africa alone (Fitzpatrick et al., 2015). Most require definition of thresholds, e.g. onset defined as the first of two consecutive days receiving at least 1 mm of rain whose total is greater than 20mm (Marteau et al., 2009), whilst an additional criterion of having no seven day period of total rainfall receiving less than 5 mm in the succeeding 20 days is added to avoid detection of false onset.

Threshold-based measures are appropriate for local agronomic studies based on station data, as they are designed to take into account availability of soil moisture. However thresholds cannot be universally determined (Fitzpatrick et al., 2015). They are also sensitive to bias and resolution, a significant issue for climate models with biases not just in overall totals but in daily rainfall distributions (Dai, 2006), such that even defining a dry day in a model is nontrivial. Given these issues applying threshold-based measures to model data, and the fact that the calculated dates are quite sensitive to thresholds (Boyard-Micheau et al., 2013), this approach is not used here.

An alternative method is based on diagnosing the date of shifts in large-scale dynamics. This has been applied to seasonal forecasts of the west African Monsoon (Vellinga et al., 2013), where onset is defined as the timing of the jump of the maximum rainfall band from the Gulf of Guinea to north of 10°N. This method is insensitive to model biases, can be diagnosed from variables other than precipitation (such as outgoing longwave radiation) and is appropriate for west Africa, where onset is associated with large-scale circulation changes. However it is not clear how to implement this method for east Africa, where no such large-scale changes have been identified.

Of the studies which have considered onset over parts of east Africa, most follow a method similar to that first used by Liebmann (Liebmann and Marengo, 2001), hereafter the Liebmann method]. This defines onset and cessation as the global minima and maxima of a timeseries, either a principal component timeseries based on station rainfall (Camberlin and Okoola, 2003; Camberlin et al., 2009) or an accumulation of daily precipitation anomalies (Dunning et al., 2016). The method is local, appropriate for gridded and model data and recently has been applied across Africa, where it has been shown to be robust across observational datasets and consistent with local agronomic threshold-based definitions (Dunning et al., 2016). In addition, using global minima and maxima ensures false onset is taken in to account. The reader is referred to (Dunning et al., 2016) for a graphical representation and further discussion of the Liebmann method.

The Liebmann method is applied here to a window centred on each season (i.e. February–June and September–December): a month either side of the main season is included in order to capture early onset and late cessation. Daily anomalies are calculated relative to the long term mean over that window, and the minima and maxima of their accumulation is used to define onset and cessation. The first five months of hindcast data for each of the 1st February and 1st September start dates are used, and CHIRPS data is treated in the same way.

Mean dates are calculated from daily climatologies, individual years and ensemble members. Simulated and observed interannual variability is compared, and the correlation of ensemble mean predictions against observations is assessed. In addition, the relationships of onset and cessation over Kenya and north Tanzania with both local seasonal total

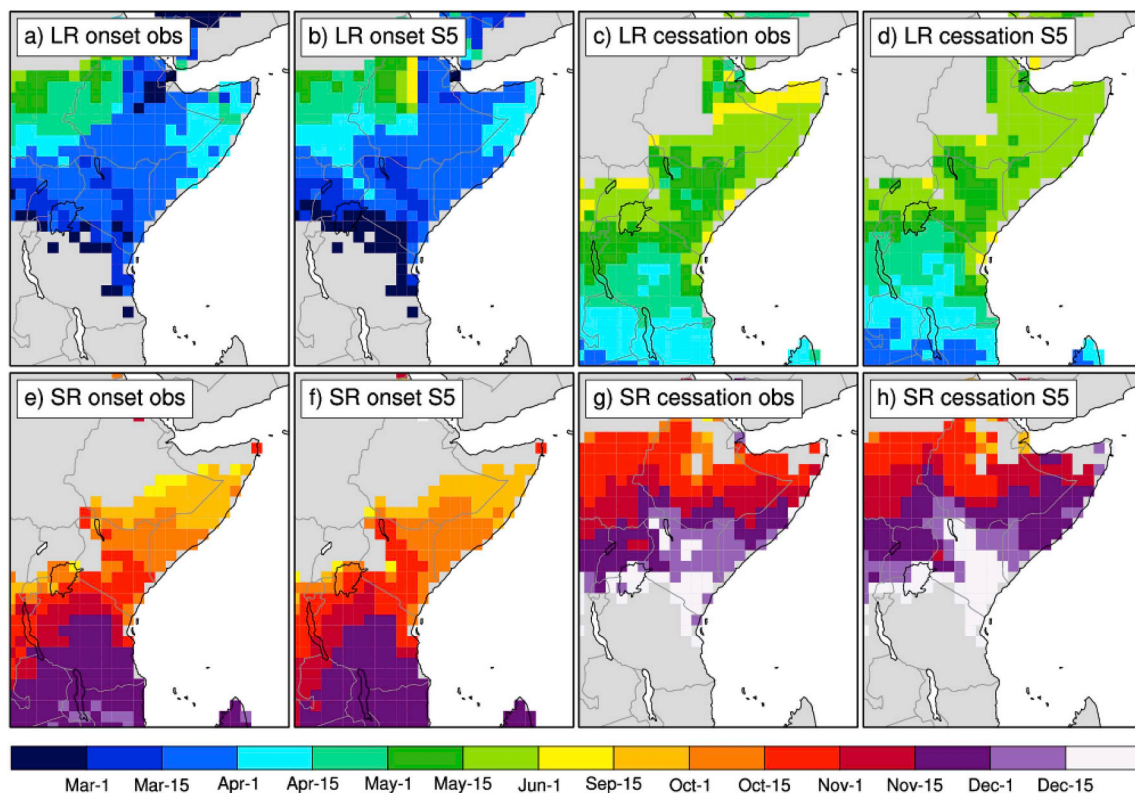


Fig. 1. Mean dates of onset and cessation in S5 (1981–2016) and in CHIRPS, calculated from daily climatology. Results for the long and short rains are shown in the top and bottom rows respectively. From left to right in each row: S5 onset, CHIRPS onset, S5 cessation, CHIRPS cessation. Points where the onset/cessation date is undefined, i.e. falls outside of the five month window for each season, are shown in grey.

and equatorial zonal winds previously described (Camberlin and Okoola, 2003) are examined over the larger region, in observations and the model hindcasts.

3. Results

3.1. Reproducing mean and variability in onset and cessation

Average onset and cessation dates are shown in Fig. 1 for S5 and CHIRPS. CHIRPS indicates long rains onset moving gradually northwards in March, followed by cessation and short rains onset moving southward from around September/October, followed by cessation a few months later. This pattern is in agreement with previous studies shown elsewhere for the region (Camberlin and Okoola, 2003; Camberlin et al., 2009; Philippon et al., 2015; Dunning et al., 2016), and is well reproduced in S5. For most of the region, the bias is less than seven days (Fig. 2), though the mean S5 onset on the Kenya/Tanzania border is several weeks too early, and over the Ethiopian highlands is several weeks too late. Standard deviations are shown in Fig. 3, which are broadly consistent with previous work which has found larger variability in the short rains. Variability overall is higher in this study, though the results are not directly comparable as they are based on different data and a different period (1958–1987 compared with 1981–2016). S5 reproduces the spatial pattern, however shows significantly higher variability for long rains cessation over the arid regions of the northeast. The mean and variability in onset and cessation dates were also computed for the S5 + ER hindcast and found to closely match that of S5 (Supplementary Figs. 1–4), though S5 + ER gives slightly larger variability in onset date across the two seasons, and slightly less variability in cessation date.

It is found that the Liebmann method sometimes has a problem automatically identifying onset. If the last part of the period is dry, sufficient negative anomalies are accumulated after cessation that the

minimum across the five months is at the end and onset is incorrectly placed here. To fix this when it occurs, the final few dry days are discounted and a new search for a global minimum gives a correct placement of onset date. The converse problem and fix is also implemented when the first part of the period is particularly dry and cessation is incorrectly placed at the start.

However, for some years the Liebmann method gives both an undefined onset and cessation. When an individual year is extremely dry, the accumulation of daily anomalies continually declines without increasing sufficiently to define a global maximum and minimum beyond the first and last points. These cases indicate a failed rainy season. The number of years for which this occurs is shown in Fig. 4; unsurprisingly failure occurs more frequently in dry regions and more often for the short rains, which have larger interannual variability around a drier mean state. The location of the maximum number of failed years is different for each season, with long rains failure most common over Kenya, whilst the short rains fail more frequently and over a larger region covering Somalia, Ethiopia and Kenya. The model reproduces the overall frequency of failed seasons, (though these do not necessarily occur concurrently with the observations), although there is an underestimate of failed seasons during the short rains and an overestimate of season failure over the tip of the Horn of Africa.

The question arises of how to treat these failed years in the forecast evaluation: a verification metric calculated on a continuous variable (e.g. correlation) is not appropriate to use with missing values. Instead, before calculating correlations, the onset (cessation) date is replaced by a date two weeks later (earlier) than the otherwise latest (earliest) date at that grid point. The rationale guiding this fix is that if a season fails, a forecast indicating extremely late onset and early cessation would contain more useful information than a forecast indicating no extreme anomaly. Note that this choice of two weeks is arbitrary, however the sensitivity of results was tested across a range of values from zero to 28 days and results are found to be quite robust to this parameter (see

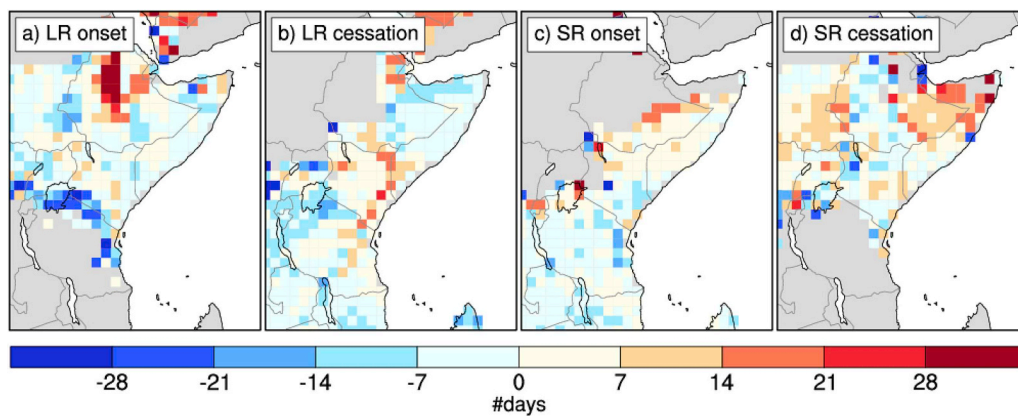


Fig. 2. S5 bias in long rains onset (a) and cessation date (b). Short rains shown in (c, d).

Supplementary Figs. 5–6). In addition this definition of a failed season allows evaluation of model's ability to anticipate failed seasons. Here the Relative Operating Characteristic Area Under Curve (ROC area, see Mason and Graham, 2002) is calculated for failed seasons.

3.2. Correlation of onset and cessation with observations

Ensemble mean correlation of onset and cessation dates are shown in Fig. 5. Correlations are shown for S5, S5 + ER and S5 + ER + 14d, indicating the forecast skill of the seasonal system, the added value of the extended range system and the improved forecast using later lead time. All are calculated over the ER period 1996–2015, and for S5 + ER + 14d any years with observed onset falling before the later start date are removed from the sample.

For the long rains onset S5 skill is generally low across the region.

Some improvement is offered with the extended range system over the highlands of Kenya. For later start dates correlations are slightly higher where the long rains start earliest: over Kenya, Tanzania and the west of Uganda, with some improved correlations over Ethiopia. For cessation correlations are even lower and neither the extended range system nor later start dates offer significant improvement.

For short rains onset the skill is much higher. Highest correlations are found over the Kenya/Somalia border, with significant correlations also over Tanzania. S5 + ER gives slight improvement over west Tanzania, whilst the later start date S5 + ER + 14d increases correlations over much of Somalia. For cessation, S5 has high correlations over Kenya, Somalia and Ethiopia, S5 + ER gives little improvement, and the later forecast start of S5 + ER + 14d increases correlations over east Ethiopia and Somalia, though correlations are reduced over Kenya.

Probabilistic verification was also carried out, considering the

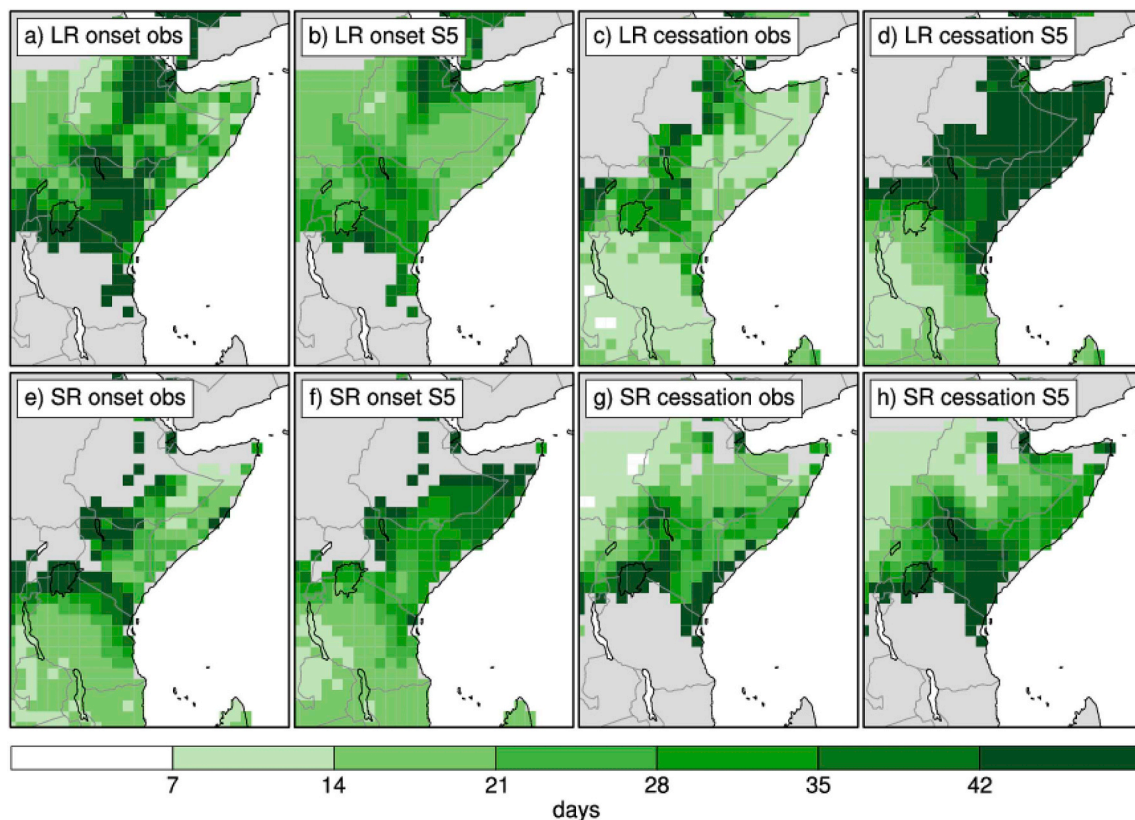


Fig. 3. As Fig. 1, for the interannual standard deviation across all hindcast years. S5 standard deviation is calculated across all years separately for each member and averaged across the ensemble.

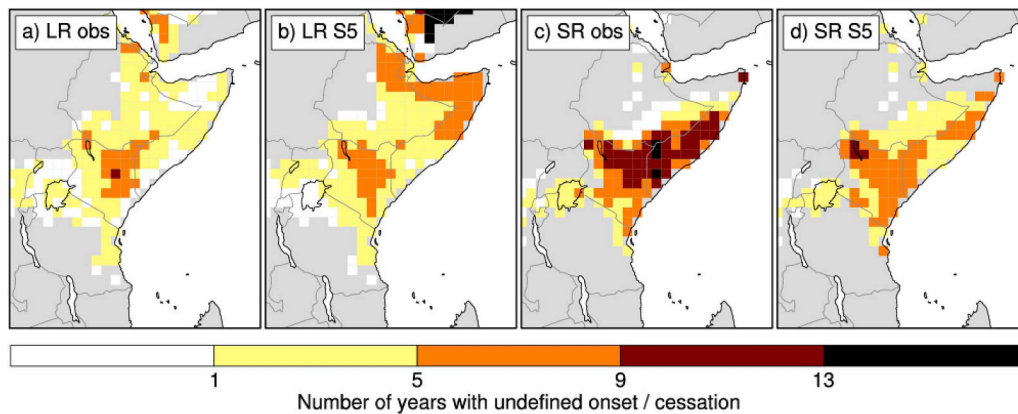


Fig. 4. Showing the number of years in the (a, b) long and (c, d) short rains for which the Liebmann method does not return onset and cessation dates for (a, c) CHIRPS and (b, d) S5, indicating failed seasons. Note that S5 is calculated as an average across all ensemble members.

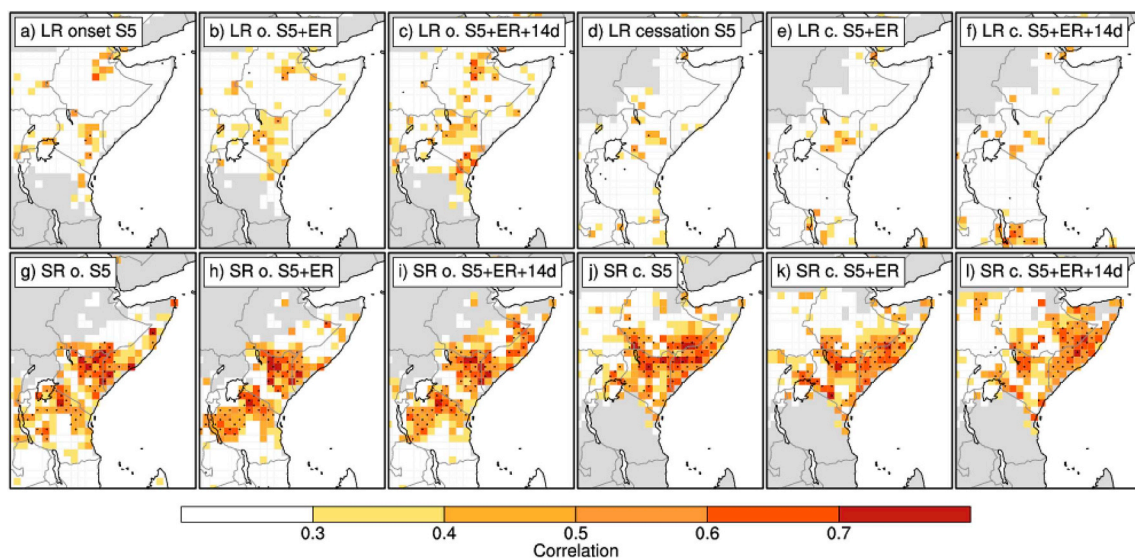


Fig. 5. Ensemble mean correlation of date forecast, against CHIRPS. (a) S5 seasonal system, issued on 1st February. (b) as (a) but with the first 46 days replaced by the extended range system (ER). (c) as (a) but using the updated ER forecast 14 days later. (d–f) as (a–c) for long rains cessation. (g–l) as (a–f) for the short rains. Stippling indicates significant values at the 95% level.

ability of the ensemble to discriminate between early and late onset and cessation, defined by tercile boundaries (see [Supplementary Figs. 7–8](#)). The pattern of skill is largely similar to [Fig. 5](#) with higher skill found for short rains, however S5+ER+14d shows better ability at detecting early long rains onset than late onset ([Fig. S7c](#)). In addition, the discrimination of early short rains cessation appears to be better near the coast, whilst late onset is better detected over northwest Kenya. In addition the model ability to discrimination of failed seasons is evaluated (see final paragraphs of section 3.2 for discussion on this point). This is shown in [Fig. 6](#). For the short rains the model is able to skillfully anticipate failed seasons where they occur most frequently, near the coast. For the long rains the model is less skillful at anticipating season failure, apart from a few gridpoints in the north of Kenya, particularly in the north west.

Seasonal total is well correlated to both onset and cessation date; overall wetter seasons tend to start earlier and finish later. This link has been demonstrated over Kenya and Tanzania ([Camberlin and Okoola, 2003](#)) and here is examined here for the whole of East Africa, in both observations and S5 ([Fig. 7](#), showing correlation of onset and cessation in the long and short rains with the MAM or OND average). A strong link between seasonal total and onset date is observed over Kenya, Tanzania and northern Ethiopia, and a weaker link over Uganda and South Sudan and lower and over the tip of Somalia. The broad pattern is

well simulated in S5, though with less variability across the region; correlations are weaker (stronger) where they are highest (lowest) in observations. The correlation of seasonal total with cessation is weaker than with onset, though S5 vastly over-represents this link.

For the short rains the strongest connection between seasonal total and onset in observations is over the Somalia/Ethiopia border, over the Kenyan Highlands and parts of Tanzania. In the dry northeast of Kenya the connection is weaker than it is during the long rains. The pattern of this link is well simulated in S5, though is slightly weaker overall. Short rains cessation is well correlated with seasonal total in observations over the Kenyan highlands, west toward Uganda and north toward South Sudan. In the northwest, over Sudan, the correlation is weaker and below significance. S5 simulates the spatial pattern of the correlation, however is too strong in the northwest.

Strong correlation between seasonal total and onset/cessation suggests that the same underlying process is responsible for predictability of both. Given this, the question arises: is onset or cessation variability predictable beyond the component linked to seasonal total? To answer this question, two correlations are compared. The first is the simulated date against observed date, as has been shown up to this point. The second is the correlation of the observed date against the simulated seasonal total anomaly. If the dates simulated by the model are better correlated to the observed dates than the simulated seasonal total

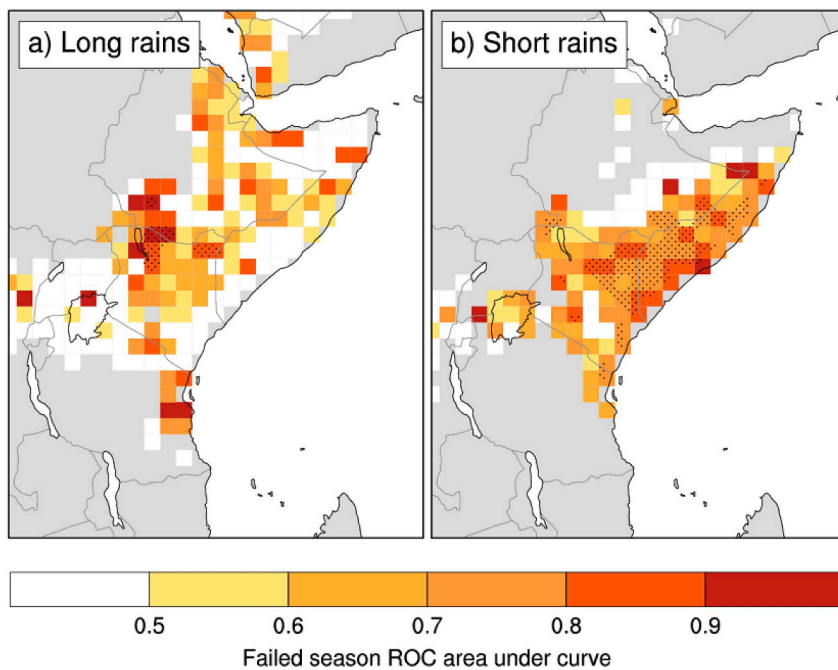


Fig. 6. Showing the model ability to discriminate failed seasons, in the long and short rains, measured by the ROC area. Significance levels are calculated following the method in Mason and Graham (2002), using the percentage of years indicating failed seasons in observations as a baseline frequency of the event for each gridpoint separately.

anomaly, this suggests that there is information in the predictions beyond variability in seasonal total.

Results are shown in Fig. 8. Overall, the two correlations are very similar, for onset and cessation across both seasons. For long rains cessation using the actual date gives slightly higher correlations for a few points on the Kenya/Ethiopia border, whilst using the actual date for short rains cessation gives higher correlation on the Kenya/Uganda

border. But for most regions, the skill of the standardised anomaly of the predicted total as a predictor of onset/cessation is statistically indistinguishable from the skill of using the actual dates predicted by the model. This result suggests that any processes responsible for variability in onset/cessation date beyond that linked to seasonal total are either not represented in the model or predictable at this timescale.

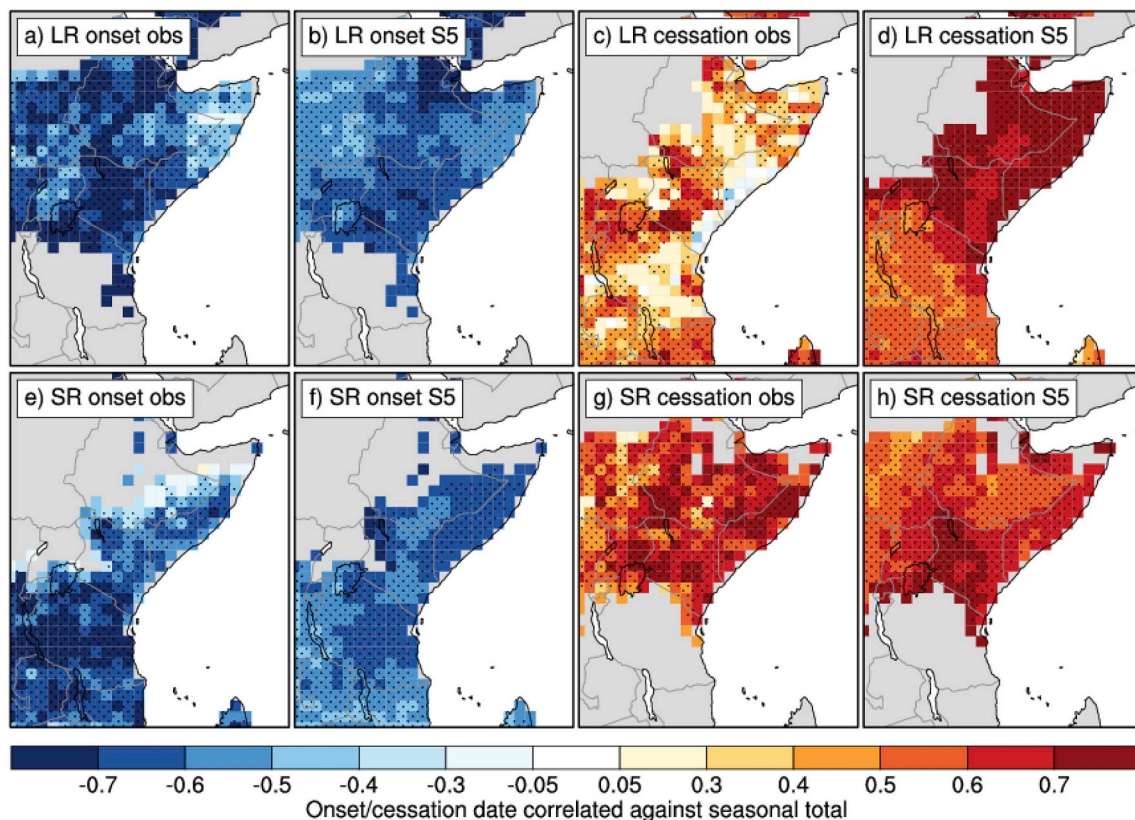


Fig. 7. Relationship between seasonal total and onset/cessation date. Stippling indicates significant values at the 95% level. Layout as Fig. 1.

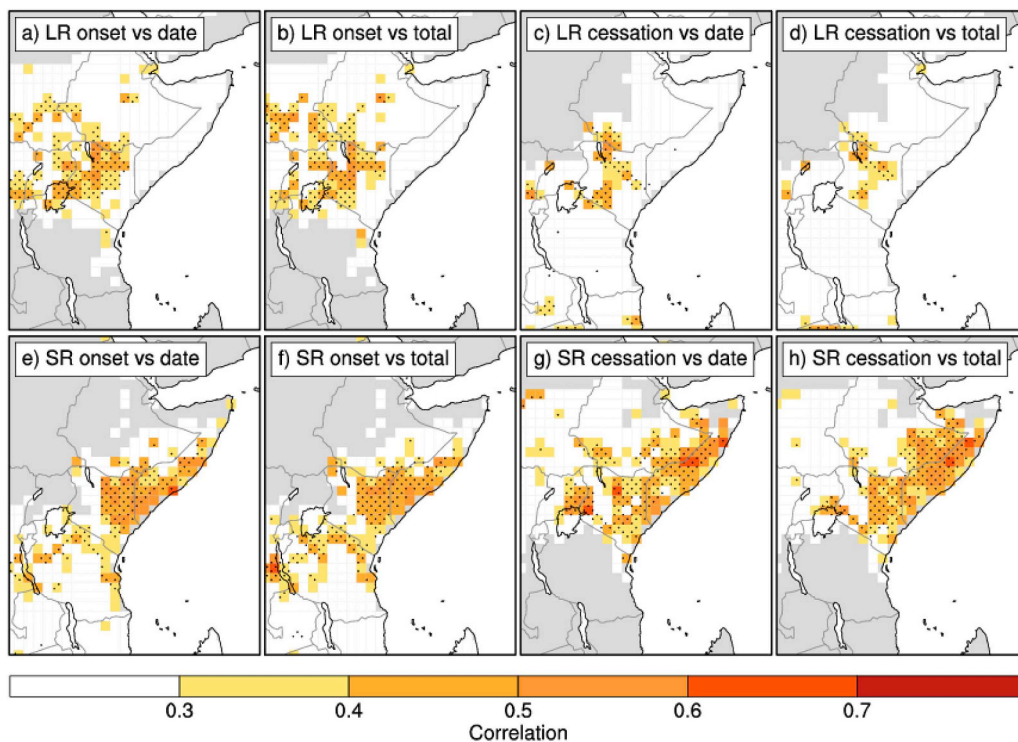


Fig. 8. Is the model predicting more than the seasonal total? (a) S5 long rains onset vs CHIRPS onset, (b) S5 long rains total vs CHIRPS onset. (c, d) as (a, b) but for long rains cessation. (e–h) as (a–d) but for the short rains. Stippling indicates significant values at the 95% level. Note that unlike Fig. 5, the whole S5 hindcast 1981–2016 is used here.

3.3. Links with zonal wind

Equatorial zonal winds are linked with onset over Kenya and Tanzania (Okoola, 1999; Camberlin and Okoola, 2003). Camberlin and Okoola (2003) define a zonal wind index (hereafter ZWI, the 700mb zonal wind averaged over 20–35E, 5S–5N) and find a correlation of this ZWI during March with onset of -0.75 . Here the same index is used to investigate this link across the wider region, for short rains onset and for cessation during both seasons. March ZWI is correlated with long rains onset, and May ZWI is correlated with long rains cessation. Similarly, October and December values of ZWI are correlated with short rains onset and cessation. ZWI in ERA-Interim is correlated against CHIRPS onset and cessation, whilst ZWI and onset/cessation are correlated with each in each S5 ensemble member.

Results are shown in Fig. 9. A negative correlation between ZWI and long rains onset is found over the southern part of Kenya, consistent with results found in Camberlin and Okoola (2003). A positive correlation is found over South Sudan and low correlation elsewhere. In S5 a negative correlation is present, though this is situated further west compared to observations, over the Kenya/Uganda border. The positive correlation between ZWI and long rains onset over South Sudan is not found in S5. For long rains cessation a large positive correlation is found across the region inland and negative correlation is found near the coast, indicating equatorial westerlies linked to late cessation inland and early cessation near the coast. This correlation is much weaker in S5 and barely above significance. Both CHIRPS and S5 have the highest correlation over western Kenya, but the observed link over the Somalia/Ethiopia border is not found in S5. S5 does not show this negative correlation with zonal winds near the coast.

The link between onset and the ZWI is quite different during the short rains. Correlations are positive over the Kenya/Somalia border but otherwise low. S5 shows a very weak link here and also shows unrealistic negative correlation over northern Tanzania and west Kenya. For cessation, the link with ZWI is highly positive over most of the region and well represented in S5, though the correlation in S5 is too weak over Somalia.

An interesting comparison can be made between ZWI-cessation and

seasonal total-cessation, which is more similar during the short rains than the long (Fig. 8g–h and 9g–h). This suggests that the common predictable factor underlying short rains cessation and short rains total is mediated largely through equatorial zonal wind anomalies, whilst long rains cessation is modified by the additional influence of the Indian monsoon.

4. Conclusion

The representation and skill of onset and cessation forecasts over east Africa in ECMWF long lead forecasts has been assessed. Mean dates found in observations are consistent with previous work (Camberlin and Okoola, 2003; Camberlin et al., 2009) and the forecasts show a bias of less than one week across most of the region, though simulate onset a few weeks too early (late) around the Kenya–Tanzania border (over parts of the Ethiopian highlands). The spatial pattern of the interannual variability in dates in the model is generally correct though variability is generally too large, particularly for long rains cessation.

In dry years over arid regions method for determining onset and cessation date fails. This provides a novel criterion to identify failed rainy season and indicates that some regions near the Somalia/Ethiopia border experience a poor rainy season in almost 50% of years. Based on this failed season metric, the model shows significant ability to identify in advance failed seasons. For the long rains failed seasons in northwest Kenya are anticipated accurately, whilst for short rains significant skill at predicting failed seasons is found over most of Somalia and northwest Kenya.

Statistically significant correlations for the magnitude of anomalous onset and cessation are found for both seasons. Higher correlations are found for the short rains, consistent with studies of predictability of seasonal rainfall totals [e.g. Nicholson, 2014]. Updating the forecast with the subseasonal system gives slightly increased correlation over some regions, particularly over the Kenya–Tanzania border during the long and Somalia during the short rains.

It is found that skill is just as high if the predicted seasonal total is used as a proxy for onset or cessation date. This suggests that a common factor is responsible for most variability in onset/cessation and seasonal

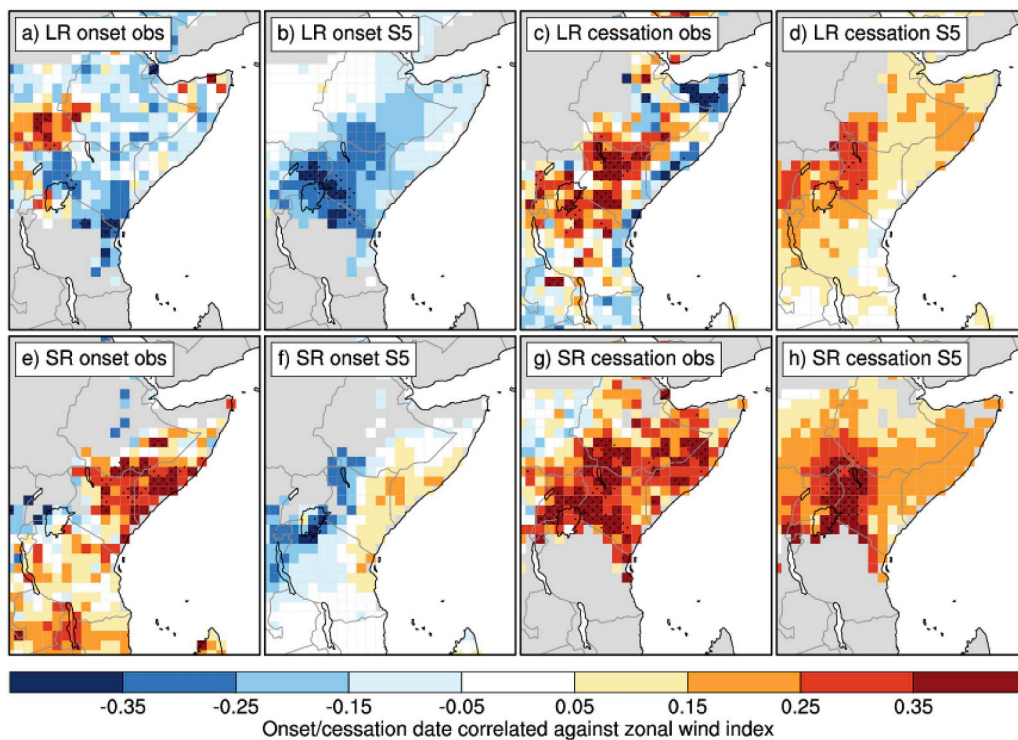


Fig. 9. Correlation between onset/cessation dates and monthly average zonal wind averaged over 5S–5N, 20–35E. The March/May and Oct/Dec monthly average of the zonal wind is used to calculate the zonal wind index, for long rains onset/cessation and short rains onset/cessation. Zonal winds from ERA-Interim are correlated with CHIRPS onset/cessation dates; S5 winds and dates are calculated once for each member and averaged over all members. Stippling indicates significant values at the 95% level. Layout as Fig. 1.

total and the model does not represent variability beyond this. Though this study is only of a single model, it does suggest that caution must be taken with an onset/cessation forecast which is ‘inconsistent’ with the seasonal forecast (e.g. late onset but high seasonal total), as no evidence has been found here that there is predictability for onset or cessation beyond the link with seasonal total.

The physical processes underlying model skill for predicting seasonal totals have been outlined in the literature. The short rains are well known to have higher predictability being largely driven by variations in the Indian Ocean Dipole and ENSO [e.g. Nicholson, 2017b], whilst the long rains are consistently seen to be less predictable at seasonal scale, having weaker teleconnections to predictable large-scale coupled SST processes (although recently the Madden-Julian Oscillation, the Quasi-biennial Oscillation and SSTs in the northwest Indian Ocean have been shown to drive a large part of the interannual variance in long rains totals (Vellinga and Milton)). Given the link outlined above between seasonal total and onset/cessation and the consistent pattern of high and low skill for the short and long rains, it is reasonable to assume that the factors providing predictability for seasonal totals also play a role in providing any predictability for onset and cessation.

The exact pattern of the relationship of onset and cessation with seasonal total has been determined here across east Africa, for observations as well as the model hindcasts. Results are consistent with those reported in the literature (Camberlin and Okoola, 2003) for onset over Kenya and north Tanzania. Correlation of long rains total with cessation is far too strong in the model over most of the region, and the correlation with onset is too strong over the tip of Somalia. The correlation of short rains total with cessation is also too strong over Sudan/South Sudan which in observations is not significant.

The relationship of onset with equatorial zonal winds (Camberlin and Okoola, 2003) is also extended to the wider region, and expanded to consider cessation. Observed links are described and though the model reproduces aspects of these connections, notable deficiencies are found. In particular the correlation is the wrong sign over South Sudan for long rains onset, and the negative correlation between zonal winds and coastal cessation is not found in the model. The link between equatorial zonal wind in October and short rains onset is very different

in the model and observations. This suggests unrealistic atmospheric dynamics and can inform future processed-based model development in the region.

Though the ability of an operational forecast system to anticipate anomalous onset and cessation has been demonstrated, further work is needed to translate to decision-relevant information [e.g. Coughlan De Perez et al., 2015]. A first step might be to establish relevant anomaly thresholds leading to significant impacts (e.g. onset delayed by two weeks). Based on these thresholds, hit and false alarm rates can be calculated, and preventative interventions and actions selected to minimise action costs and losses. In this process it is important to be clear with users about the level of forecast skill achievable: a forecast with statistically significant correlations does not necessarily have value. However where value can be demonstrated forecast information may be exploited, leading to improved anticipation, reduced risks and increased societal resilience to climate hazards.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at <http://dx.doi.org/10.1016/j.wace.2018.05.003>.

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