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Impact-based seasonal rainfall forecasting to trigger early action for droughts

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ABSTRACT

The Horn of Africa faces an ongoing multi-year drought due to five consecutive failed rainy seasons, a novel climatic event with unpreceded impacts. Beyond the starvation of millions of livestock, close to 23 million individuals in the region are currently facing high food insecurity in Kenya, Somalia and Ethiopia alone. The severity of these impacts calls for the urgent upscaling and optimisation of early action for droughts. However, drought research focuses mainly on meteorological and hydrological forecasting, while early action triggered by forecasts is seldom addressed.

This study investigates the potential for early action for droughts by using seasonal forecasts from the European Centre for Medium-Range Weather Forecasts (ECMWF) SEAS5 system for the March–April-May (MAM) and October–November-December (OND) rainy seasons. We show that these seasonal rainfall forecasts reflect major on-the-ground impacts, which we identify from drought surveillance data from 21 counties in Kenya. Subsequently, we show that the SEAS5 drought forecasts with short lead times have substantial potential economic value (PEV) when used to trigger action before the OND season across the region ($PEV_{max} = 0.43$). Increasing lead time to one or two months ahead of the season decreases PEV, but the benefits persist ($PEV_{max} = 0.2$). Outside of Kenya, MAM forecasts have limited value. The existence of opportunities for early action during the OND season in Kenya and Somalia is demonstrated by high PEV values, with some regions recording PEV_{max} values close to 0.8. To illustrate the practical value of this research, we point to a dilemma that a pastoralist in the Kenyan drylands faces when deciding whether to adopt early livestock destocking.

This study underscores the importance to determine the value of early actions for forecast users with different action characteristics, and to disseminate this value alongside the standard forecasts themselves. This allows users to trigger effective actions before drought impacts develop.

1. Introduction

Over the last decades, droughts have heavily impacted communities in East Africa. The ongoing drought, which began in 2020, is unprecedented. Most regions have experienced five consecutive failed rainy seasons, which is a climatic episode that has not been seen in at least 40 years (World Meteorological Organization (WMO), 2022; IGAD Climate Prediction and Applications Centre (ICPAC), 2023). The current figures are worse than those observed during the 2010–2011 drought, with recent estimates indicating close to 23 million people are facing high levels of food insecurity in Ethiopia, Kenya and Somalia (ICPAC, 2023). The majority of the population of the region is highly dependent on rainfed agriculture, occurring during the March–April-May (MAM) and the October–November-December (OND) rainy seasons. Below-normal rainfall during these seasons frequently leads to crop failures and water shortages (Meza et al., 2020), which have a considerable impact on the population. The 2008–2011 drought in Kenya caused a staggering USD 12.1 billion loss to the Kenyan economy (Government of Kenya, 2012). The Famine Early Warning Systems Network (FEWS-NET) reports a dramatic increase in the number of food-insecure individuals in the region (Funk et al., 2019). Agro-pastoralists who live in the arid and semi-arid lands of East Africa are especially vulnerable to droughts, because their resource endowments are highly dependent on rainfall. Over the last few decades, these communities have suffered from changing and unreliable rainy seasons. Rainfall during the MAM season has been dramatically declining since 1999 (Funk et al., 2019; Lyon and

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Dewitt, 2012; Maidment et al., 2015; Liebmann et al., 2014). This makes it more difficult to anticipate the rainfall necessary to make important crop and livestock production decisions, and complicates other forms of drought adaptations (Ndiritu, 2021).

Therefore, early-warning systems are increasingly important for the region, especially to help prepare for droughts through their ability to trigger early actions before drought impacts develop (Food and Agriculture Organization of the United Nations (FAO), 2019). Compared to late responses to disasters, early-warning and early-action systems provide a higher return on investments (Global Commission on Adaptation, 2019). Impact assessments and modelling studies have indicated that early action can be highly cost effective for agro-pastoralists in East Africa, relative to late responses (e.g. Cabot Venton et al., 2012; Bekele and Abera, 2008). These actions include planting drought-resistant seeds, purchasing and storing fodder, destocking, water harvesting and migration (Gebeyehu et al., 2021; Rasmussen et al., 2014).

Significant progress has been made on meteorological and hydrological forecasting in the region. Three times a year the ICPAC releases seasonal temperature and rainfall forecasts during the Greater Horn of Africa Climate Outlook Forums (GHACOFs). Furthermore, hydrological forecasts from TAMSAT-ALERT (Asfaw et al., 2018) are used to predict soil moisture and agricultural production indicators such as the Water Requirement Satisfaction Index (WRSI). Much research has focused on evaluating the skill of these forecasting systems, such as for the ICPAC (Walker et al., 2019), the European Center for Medium-Range Weather Forecasts (ECMWF) SEAS5 (MacLeod, 2019; Mwangi et al., 2014) and TAMSAT (Boult et al., 2020) forecasts.

Despite these particular investments in early warning systems, early actions are still insufficiently leveraged and suffer from a lack of scientific foundation (Lopez et al., 2020). This also counts for areas in the Horn of Africa, including vulnerable agro-pastoral regions (FAO, 2018a). Forecasts should be tailored and tested to represent relevant on-the-ground impacts, leading to impact-based forecasts. However, just a few studies conceptually described (Boult et al., 2022; Tozier de la Poterie et al., 2023) or developed and tested such impact-based forecasts for droughts (e.g. Sutanto et al., 2019; Westerveld et al., 2021). Studies on evaluating actions taken on these forecasts are even more scarce. Little is known about the manner in which forecasts may be translated into concrete early action triggers and recommendations for forecast users. The existing studies on this matter all concern floods (e.g. Bischiniotis et al., 2020, 2019; Coughlan De Perez et al., 2016, 2015; Lopez et al., 2020). This lack of a scientific foundation on early action for droughts hampers the development of guidelines and advisory documents, such as context-specific Early-Action Protocols (EAPs). This is one of the reasons why only some African countries have approved national EAPs for drought (International Federation of Red Cross and Red Crescent Societies (IFRC), 2023).

The present study addresses this knowledge gap. The aim of the study is to assess the value of seasonal rainfall forecasts from the ECMWF SEAS5 system to trigger action ahead of a drought during the MAM and OND rainy seasons in the Horn of Africa. We have developed a framework to assess how these forecasts can be used effectively for (lead time-dependent) decision-making. The methods and the results support the development of drought EAPs and other early action guidelines for the region.

We first describe the Horn of Africa as a case-study area. Thereafter, we explain the main steps that we took by presenting our methodological framework. Subsequently, we describe the input data, the forecasts that we use and the impact of droughts, and we develop our analysis of early action. The results outline the development of impacts during drought, and the value for early action for users with different characteristics. This includes a demonstration about how a pastoralist in Kenya can use our findings in practice to make livestock destocking decisions. Finally, we discuss and summarise our findings, and we provide recommendations for future work.

2. Case study area

2.1. Topography

The Horn of Africa (HoA) is the outermost peninsula of East Africa, and we refer to it here to indicate the territories of Kenya, Somalia and Ethiopia. The region has considerable topographic variability, with a high mountain plateau in western Ethiopia (the Ethiopian Highlands) and mountains in central (the Mount Kenya region) and south-western Kenya. The rest of the region is characterised by low-lying arid and semi-arid lands that extend over large parts of Kenya and Somalia (Cabot Venton et al., 2012).

2.2. Climate and rainfall

The HoA is characterised by low and irregular rainfall which is strongly concentrated in the rainy seasons. Most of East Africa is characterised by dual-wet OND and MAM seasons, with the latter being the wettest season overall (Nicholson (2017), Fig. 1, top). Some regions have more uniform rainfall over the year, such as the Ethiopian Highlands and the south-eastern tip of Kenya (Seregina et al., 2019). Precipitation in the OND season is largely influenced by large-scale climatic oscillations, such as the El Niño–Southern Oscillation (ENSO) and the Indian Ocean Dipole (IOD; Liebmann et al., 2014). The climatic drivers of rainfall in this season are relatively well understood. However, much uncertainty surrounds the drivers of rainfall in the MAM season (Liebmann et al., 2014; Rowell et al., 2015). This results in the OND season being more predictable than the MAM season, a proposition that holds true for both total rainfall (MacLeod, 2019) and rainfall onset and cessation (MacLeod, 2018). Analysis of the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS, Funk et al., 2015) data on rainfall climatology reveals changes in the MAM and OND rainfall seasons. OND rainfall is increasing in large parts of the region (Fig. 1, bottom left), while MAM rainfall shows the opposite trend (Fig. 1, bottom right). Seasonal meteorological droughts become more (for MAM) and less (for OND) severe over most of the HoA (Fig. 1, bottom). These trends are consistent with previous research on the changing dynamics of those seasons (Nicholson, 2017; Rowell et al., 2015; Seregina et al., 2019). However, the factors that cause the decline of MAM rainfall and their connection to climate change remain uncertain (Rowell et al., 2015).

2.3. Community adaptation to drought

The main livelihood in the HoA region is (agro-)pastoralism (Cabot Venton et al., 2012; Coughlan de Perez et al., 2019), which is often the most suitable option for communities to maintain a viable livelihood in drylands (FAO, 2018a). Across the HoA, these populations are under pressure from droughts (Government of Kenya, 2012). The region faced 18 periods of famine between 1900 and 2011 (Cabot Venton et al., 2012), with the 2008–2011 famine and the ongoing 2020–2022 drought being the most recent significant disasters. The communities have developed a wide array of adaptations and coping strategies, including migration, the diversification of livestock, destocking, economic diversification, emergency water and feed supplementation, and the distribution of drought-resistant seeds (FAO, 2018a; Government of Kenya, 2021; Opiyo et al., 2015).

3. Methods

We designed a methodological framework to assess the societal impact of rainfall anomalies, seasonal forecast skill and eventually an evaluation of forecast value for early action (Fig. 2). We used CHIRPS rainfall data for the last 40 years (1981–2020) and assessed how the impacts of drought develop as a result of rainfall deficits by using a variety of different indicators (Fig. 2, top left). We derived a range of

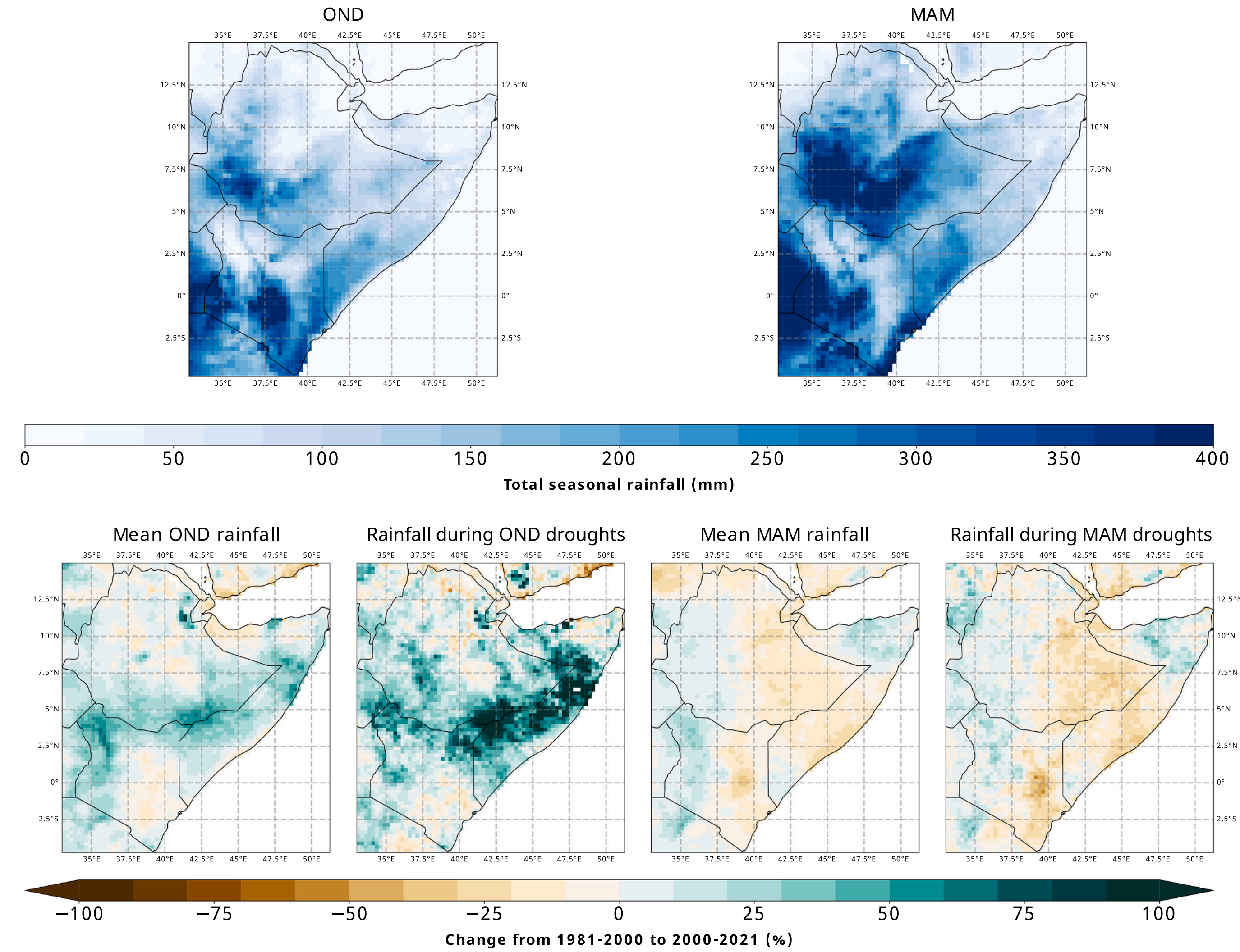

Fig. 1. The CHIRPS rainfall climatology for the OND (left) and MAM (right) rainy seasons in the HoA region, expressed as the total seasonal rainfall climatology (mm) from 1981 to 2021 (top). Change of mean total rainfall and rainfall droughts (<33rd percentile) from 1981 to 2000 to 2000–2021 is also displayed (bottom). Note that a relatively small change in precipitation can already result in large percentual differences in very arid regions.

rainfall indicators with specific thresholds to examine their relationship with on-the-ground drought impacts. We used ensemble hindcasts from the ECMWF SEAS5 forecasting system and calculated the same rainfall indicators from these forecasts (Fig. 2, top right). Finally, we compared observations and forecasts in a verification analysis to calculate a relative operating characteristic (ROC) skill score (Fig. 2, centre). We used this forecast skill in a potential economic value analysis to calculate the value of using SEAS5 forecasts to trigger early action for droughts (Fig. 2, bottom).

3.1. Rainfall data and indicators

We used rainfall observations from the global CHIRPS dataset (Funk et al., 2015), which provides daily rainfall values on a 0.05-degree grid over a period stretching back to 1981. CHIRPS is widely accepted as a valuable rainfall product for East Africa (Dinku et al., 2007; Seregina et al., 2019). We downloaded ECMWF SEAS5 seasonal hindcasts (Johnson et al., 2019), which cover the period between 1981 and 2020, by using the ECMWF web API (ECMWF, 2022). These hindcasts have a lead time up to 7 months (up to 13 months quarterly, but not used here), a horizontal resolution of 0.4 degrees on a latitude-longitude grid, and they contain 25 ensemble members. They are initiated every month and produce forecasted accumulated total precipitation amounts for each day. A number of processing steps were required to compare CHIRPS rainfall with the ECMWF forecasts in the forecast verification and economic value analysis. First, we disaggregated the daily accumulations in the ECMWF forecasts to daily amounts of precipitation. The spatial resolution of the CHIRPS rainfall dataset was reduced to 0.4 degrees to match the resolution of ECMWF, using a linear interpolation technique. We subsequently calculated seasonal rainfall indicators for the ECMWF forecasts and CHIRPS observations for the MAM and OND seasons. These indicators are 1) total seasonal rainfall, 2) the number of wet days (> 1 mm/day) and 3) the maximum length of dry spells. A dry spell is defined as a period of at least five consecutive dry days (< 1 mm/day). Subsequently, these absolute indicators were converted to quantiles. We use different drought severity classes using a range of quantile thresholds (0.1, 0.2, 0.3rd) in the climatological distribution for each rainfall indicator separately.

3.2. Drought impacts

We added on-the-ground and remotely sensed drought-impact data to allow for impact-based forecasting and early-action analysis. For the on-the-ground drought-impact indicators, we digitised nine years (2013-2021) of monthly text-based early-warning bulletins from the National Drought Management Authority (NDMA) for 21 counties in Kenya

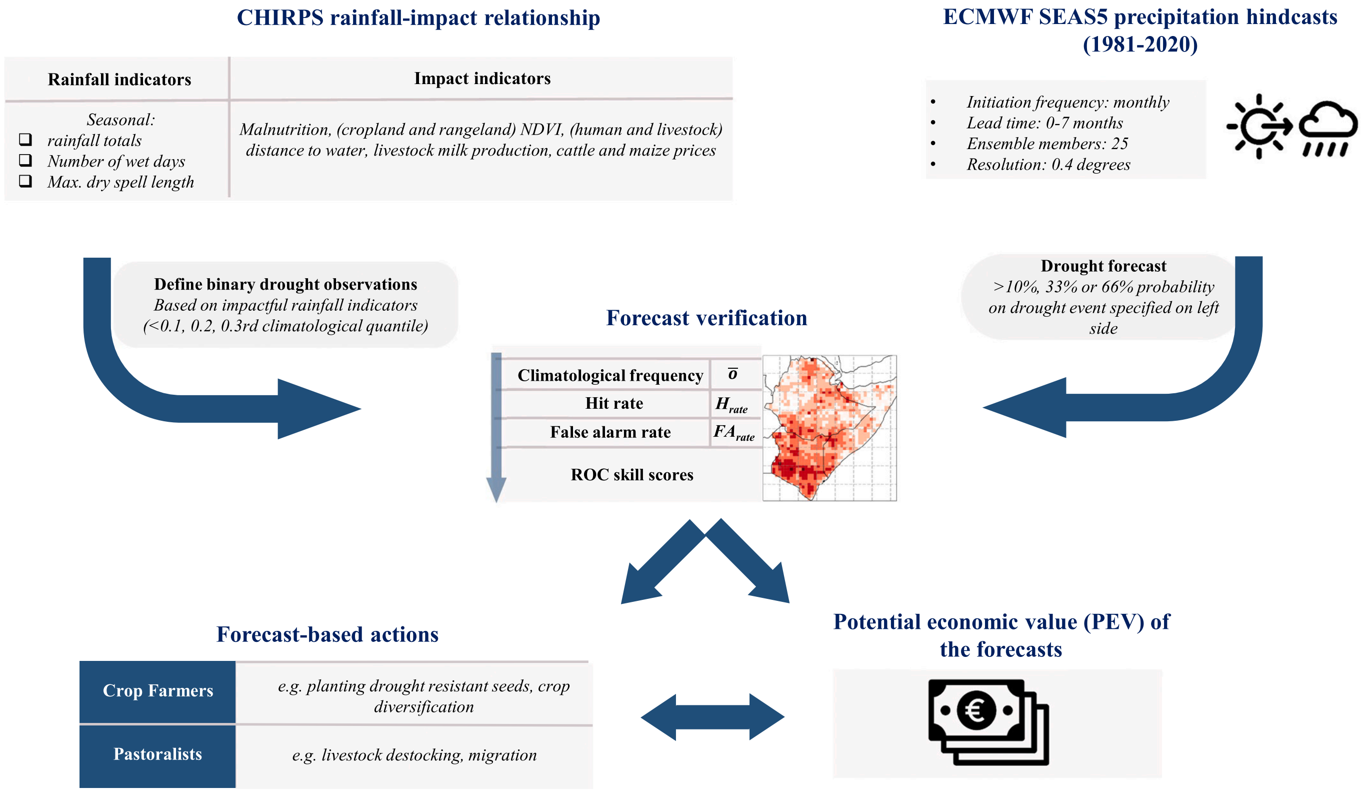

Fig. 2. Framework illustrating the research methodology, including the drought impact analysis (top-left), seasonal climate forecasts (top-right), drought forecast verification (middle), potential early-actions (bottom-left) and the resulting potential economic value (bottom-right).

(NDMA, 2022). This community data represents six impact indicators: 1) livestock milk production (liter/household/month), 2) cattle prices (Kenyan Shilling, KSh), 3) maize prices (KSh/kg), 4) human distance to water sources (km), 5) livestock distance to water sources (km) and 6) the percentage of children (<5 years old) at risk of malnutrition (see Fig. A.1). For the 2000–2021 period, we also included the Normalized Difference Vegetation Index (NDVI, Bannari et al., 1995) as a drought indicator, derived from the NOAA STAR Center for Satellite Applications and Research (NOAA, 2021). This dataset contains data from the Advanced Very High Resolution Radiometer (AVHRR) sensor, which is mounted on a constellation of NOAA polar-orbiting satellites. The archive contains validated seven-day composites of smoothed NDVI data in 4 km resolution. Besides total area NDVI, we calculated NDVI values for rangeland and cropland specifically, resulting in three different indicators: overall NDVI, rangeland NDVI and cropland NDVI. The last two were obtained by using crop and rangeland masks (Pérez-Hoyos, 2018) and primarily capture the dynamics of agricultural vegetation. Impact and NDVI indicators are continuing to be collected on monthly bases.

Meteorological droughts during the MAM and OND rainy seasons will affect these impact indicators. Droughts in East Africa can lead to increases in maize prices at local markets, primarily as a consequence of decreased supply due to crop failures (Government of Kenya, 2021). The distance to water sources typically increases, which will impact both humans and livestock. The vegetation conditions will deteriorate, which can be observed through lower NDVI values. This all contributes to poorer livestock conditions, which can reduce the livestock milk production and cattle prices (FAO, 2018a). These various drought impacts can lead to a reduction of food security, which we measure as the percentage of children (<5 years old) at risk of malnutrition. We outline these rainfall-impact relationships in Section 4.1.

For each county, the aforementioned drought indicator values were ranked over the 2013–2021 period. Each month was ranked separately, and the results were expressed as impact percentiles. Generally, higher absolute values of the impact indicators resulted in higher impact percentiles. Only for the NDVI and livestock indicators (livestock distance to water, cattle prices), higher impacts are expressed as lower absolute values. Therefore, the impact percentiles of these indicators were inverted by subtracting the percentile from 100 (e.g. 30th percentile becomes 70th). The impact percentiles were resampled to the mean of three-month periods with zero-month (lag = 0; MAM and OND seasons), one-month (lag = 1; April–May-June and November–December-January), two-month (lag = 2; May, June, July and December–January-February), three-month (lag = 3; June–July-August and January–February-March) and four-month (lag = 4; July–August-September and February–March-April) delay after the rainy season.

3.3. The relationship between seasonal rainfall and drought impact

Seasonal rainfall forecasts can only trigger action effectively if their rainfall indicators cause on-the-ground impacts. Therefore, we determined whether the three seasonal rainfall indicators (see Section 3.1) used in the ECMWF SEAS5 forecast represent on-the-ground impacts on communities in Kenya. We calculated these rainfall indicators from the CHIRPS observations for the OND and MAM season, and compared them to the drought impact data from NDMA with different lag times (see Section 3.2). If the rainfall indicator for a season was below the 0.1, 0.2 or 0.3 quantile of the seasonal climatology, the season would be classified as a meteorological drought. We subsequently compared the impacts of meteorological drought and no-drought seasons to determine how well seasonal rainfall dynamics reflected drought impacts.

We used the Cohen's *d* effect size (Cohen (1988); expressed as d_s) to quantify the effect of the rainfall indicators on drought impacts in the 21 counties in Kenya. The metric returns the standardised mean difference between drought impacts in seasons of meteorological drought and seasons of no meteorological drought. This has been done for all impact indicators with the mentioned lag times, and for all rainfall indicators and thresholds, separately. A d_s of 0.5 indicates that the mean difference in impact is equal to half a standard deviation:

$$d_s = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{(n_1-1)SD_1^2+(n_2-1)SD_2^2}{n_1+n_2-2}}} \tag{1}$$

where $\bar{X}_1$, SD_1, and n_1 are the mean impact, the standard deviation and the size of the sample of impacts for seasons in meteorological drought, and $\bar{X}_2$ SD_2 and n_2 capture the same values for no-drought seasons. We calculated d by using pooled standard deviation in order to correct for differences between group means and unequal group sizes (denominator, Eq. (1)). Hence, if the group with largest standard deviation grows and the group with the smallest standard deviation shrinks, pooled standard deviation will increase and d_s will decrease. We used the benchmarks for d that were suggested by Cohen (1988): small [$d > 0.2$], medium [$d > 0.5$], and large [$d > 0.8$].

3.4. The economic value of anticipatory action

The assessment of the rainfall-impact relationships showed that seasonal rainfall total was the most important rainfall indicator for on-the-ground impact generation (see Section 4.1, Fig. 4). Therefore, we used total seasonal rainfall to define meteorological droughts for the purposes of our early-action analysis. The CHIRPS rainfall data and the ECMWF SEAS5 forecasts were resampled from daily to seasonal rainfall totals, and areas with a long-term climatology of <10 mm per season were masked out. The 33rd percentile was calculated from the CHIRPS climatology of total seasonal rainfall for both the OND and the MAM seasons, and seasons with total rainfall < 33rd percentile (i.e. lower tercile, or below-normal rainfall) were classified as drought seasons. The lower tercile rainfall threshold is classified by WMO to categorize below-normal rainfall (WMO, 2020). The 33rd-percentile threshold was also calculated for the ECMWF SEAS5 forecasts for OND and MAM. A drought would be forecast if the fraction of ensemble members falling into the <33rd-percentile category exceeded the drought probability threshold (P_t). Subsequently, the hit rate H_{rate} (H_{rate} = number of hits / total amount of drought events) and the false alarm rate FA_{rate} (FA_{rate} = number of false alarms / total amount of non-drought events) were calculated for all possible P_t values. The H_{rate} and FA_{rate} for a set of P_t thresholds were calculated for all pixels and used to form the ROC curves. It represents the ability of the system to distinguish drought events from non-drought events, as reflected in the comparison between the H_{rate} and FA_{rate}. The area under the ROC curve (ROC-AUC) is a skill score which reflects the accuracy of the forecasting system (Buizza and Hollingsworth, 1998; Mason, 1982). Perfect systems return a ROC-AUC of 1, while no-skill systems (i.e. not better than a random forecast; $H_{rate} = FA_{rate}$) return a ROC-AUC of 0.5.

The forecast verification metrics H_{rate} and FA_{rate} can be used to calculate the economic value of forecast information. The Potential Economic Value (PEV) theory is an established method for determining the long-term economic benefits of early action based on forecast information (Richardson, 2000). We will introduce the concept of this decision framework below.

Assuming forecasts are not used and the climatological frequency of drought ($\bar{o}$) is known, a user can decide to act always with the total expenses:

$$E_{Climate} = C + \bar{o}\, Lu \tag{2}$$

while if action is never implemented, total expenses are as follows:

$$E_{Climate} = \bar{o}^*\left(L_u + L_p\right) \tag{3}$$

where C = action costs, L_p = losses that could have been avoided by taking action, and L_u = inevitable drought-induced losses.

A rational user will choose the option which generates the lowest amount of total expenses. If the total expenses of permanent protection (Eq. (2)) exceed the expenses of never taking protective action (Eq. (3)), users will never take such action. It follows that $E_{Climate}$ is defined as the minimum of Eqs. (2) and (3).

When forecast information is employed, the total expenses using forecast information ($E_{Forecast}$) should be lower than the expenses only using climatological information. The difference between $E_{Forecast}$ and $E_{Climate}$ can be interpreted as the benefit of using forecast information. To calculate the PEV of the forecasts, this benefit is compared to a benchmark, which is defined as the benefit that would be obtained from perfect forecasts ($E_{Perfect}$, i.e. no false alarms (E_{12}, Table 1) or misses (E_{21}, Table 1)):

$$PEV = \frac{E_{Climate} - E_{Forecast}}{E_{Climate} - E_{perfect}} \tag{4}$$

We refer to PEV simply as the 'value' of the forecast. The expenses using forecast information ($E_{forecast}$) depend on the chosen probability trigger threshold P_t. This threshold is used to convert the ensemble forecast to a binary yes/no forecast, and will yield a specific hit rate H_{rate} and false alarm rate FA_{rate}. Richardson (2000) showed that by substituting $E_{Climate}$ (minimum of Eqs. (2) and (3)), $E_{forecast}$ and $E_{perfect}$ in Eq. (4), the PEV can be conveniently expressed using the H_{rate} and FA_{rate}:

$$PEV = \frac{min[\bar{o}, r] - FA_{rate}(1-\bar{o})r + H_{rate}\bar{o}(1-r) - \bar{o}}{min[\bar{o}, r] - \bar{o}r} \tag{5}$$

It follows that, for a certain P_t for an event with frequency $\bar{o}$, the only user-dependent variable to determine forecast value is the cost-loss ratio r (=C / L_p). C denotes the costs of acting when a drought is forecast. The loss is the drought damage that can be mitigated by taking action (L_p). Users take these early actions only if C < L_p, so only actions with C/L_p ratios between 0 and 1 are considerable. In flood risk-management studies, the costs of a protective measure are often treated as fixed (e.g. the costs of deploying temporal barriers), which are independent from flood occurrence (see e.g. Bischiniotis et al., 2019). However, for droughts the costs of action are often more complex and dependent on various factors, including whether a drought occurs. For example, pastoralists can sell livestock prior to the rainy season if drought is forecast, which results into costs due to missed milk production of livestock. However, the missed milk production – and therefore the loss of this production after selling livestock – is lower under drought conditions ($C_{drought}$; Table 1), than when a drought does not occur (C_{normal}; Table 1). For these cases, the PEV theory allows the costs of action to be differentiated across instances in which an event does or does not occur. In these cases, the cost-loss ratio definition is slightly adapted (see Section 5 in Richardson, 2003).

Table 1 shows a contingency table showing the total expenses for the combination of forecasted and observed drought occurrences. It follows that the expenses in case early action is triggered and drought occurs is equal to $C_{drought} + L_u$ (labeled E_{11}), while in case a drought does not occur these are C_{normal} (=E_{12}). If early action is not triggered and a drought occurs, total expenses are $L_u + L_p$ (=E_{21}). We assume the costs are zero if no action is taken and a drought does not occur ($E_{22} = 0$).

Table 1
Contingency table of total expenses (costs and losses) associated with different forecasts and observations of a drought event.

	Drought observed	No drought observed
Drought forecast – early action	E_{11} Hit Expenses = $C_{drought} + L_u$	E_{12} False alarm Expenses = C_{normal}
No drought forecast – no early action	E_{21} Miss Expenses = $L_u + L_p$	E_{22} Correct negative Expenses = 0

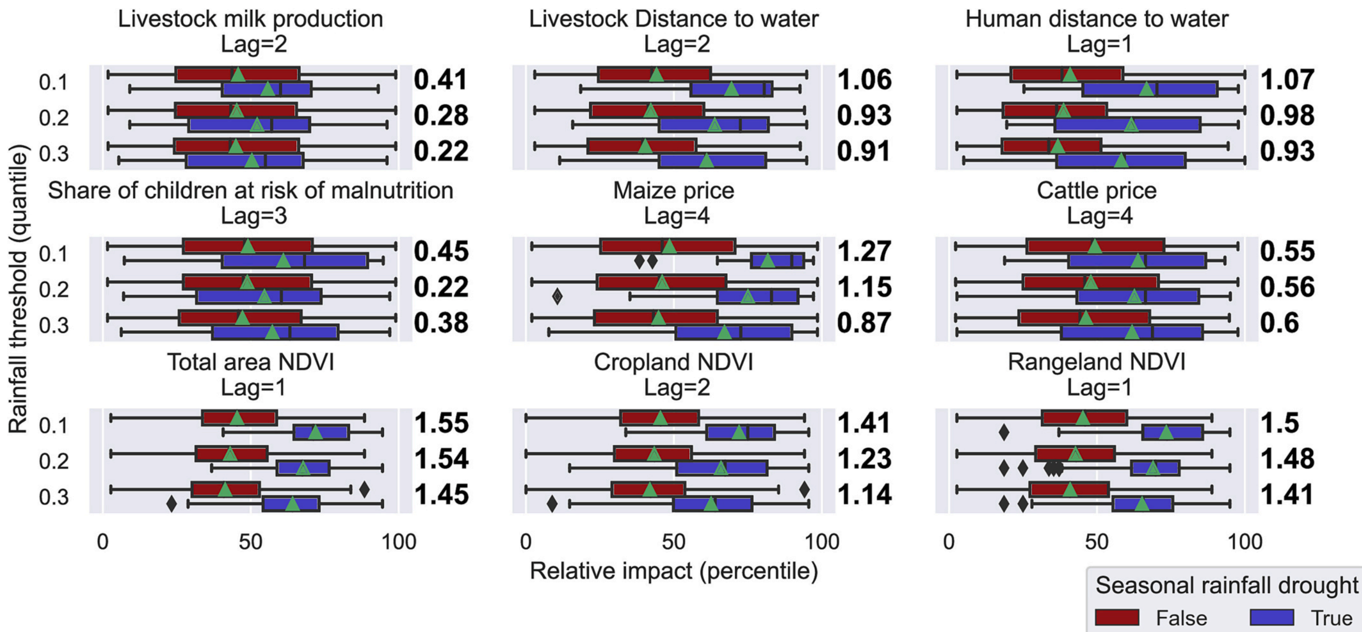

Fig. 3. The effect of MAM and OND rainfall droughts for different drought severity classes (total rainfall < 0.1, 0.2 and 0.3th quantile) on nine different drought impact indicators. Blue boxes display percentiles derived from impact indicators for meteorological drought seasons, red boxes represent non-drought seasons. Percentiles of the livestock indicators and NDVI are inverted; i.e. low NDVI, milk production and cattle prices return high relative impact. Green triangles indicate mean impact scores per category. Lag represents the number of months after the rainy seasons required for the strongest impacts to develop. Bold numbers indicate the magnitude of difference between impact indicators for seasons with meteorological drought and no-drought, expressed by the effect size d_s.

4. Results

4.1. On-the-ground development of drought impact

We found that total seasonal rainfall during the MAM and OND season has a large overall effect on impact development ($d > 0.8$). This counts for all but three indicators (livestock milk production, children at risk of malnutrition and cattle prices; Fig. 3). On average over all indicators, total seasonal rainfall has a large effect on drought impact development ($d > 0.8$; Table A.3). Drought impacts develop for all drought severity thresholds, but they generally increase with the severity of meteorological droughts (Fig. 3). Moreover, drought impacts can be discriminated better using stronger drought severity thresholds, as indicated by larger effect sizes. Indicators with a clear physical relationship with rainfall and water availability (NDVI and distance to water sources for livestock and humans) generally show a larger drought impact ($d = 0.91$–1.55) than the other socio-economic NDMA indicators ($d = 0.22$–1.27). The link between the other NDMA indicators (prices, livestock milk production and malnutrition) and rainfall is less direct, and not only influenced by droughts. External influences (e.g. global market dynamics, armed conflicts) often also play a major role (Government of Kenya, 2021). Although maize prices are normally also dependent on these external factors, we still find the impact of meteorological droughts on maize prices to be very strong ($d = 0.87$–1.27). The impacts on rangeland NDVI are stronger than on cropland NDVI. This can be explained in relationship to a stronger influence of human interventions in croplands than in rangelands, due to irrigation and harvesting practices which disturb the rainfall-NDVI relationship.

Besides total seasonal rainfall, we tested two additional rainfall indicators and their relationship with drought impact: the number of wet days and the maximum length of dry spells. We selected the 0.3th quantile to classify meteorological drought from the three different rainfall indicators to assess their relationship with impacts. Fig. 4 shows that all the rainfall indicators generated impacts, but that impacts are highest for deficits in the total seasonal rainfall indicator. In particular, distances to water sources, maize prices and NDVI have a stronger relationship with total rainfall. However, cattle prices and livestock milk production show a slightly stronger link with the number of wet days (see Fig. 4 and Table A.3). This is an indication that livestock health indicators have a stronger link to the distribution of rainfall, rather than the total amount of rainfall over the season. Drought impacts are only weakly related to the maximum length of dry spells during a rainy season (Fig. 4 and Table A.3). Impacts develop already during the MAM and OND season, but continue developing many months after the rainy season and into the dry seasons. The impacts on some indicators (NDVI and distance to water) manifests shortly after the start of the rainy season (lag of 0–1 months, red circle in Fig. 4), while others (maize and cattle prices as well as malnutrition) develop towards the end of the dry season. NDVI and distance to water are directly linked to water availability, and therefore rainfall amounts, which can explain a more rapid response to rainfall deficits, compared to prices or malnutrition, which happen further in the impact chain.

4.2. Potential economic value of drought forecasts

We used the most impactful rainfall indicator (seasonal rainfall totals) in the forecast and early action analysis. We applied the ROC-AUC skill score to verify forecasts of lower tercile rainfall (<33th percentile), and the PEV theory to translate this skill into early action. We found that the OND season has substantial skill (ROC-AUC score = 0.76) over the HoA region for forecasts initiated on October 1st (Lead 0 in Fig. 5, bottom). That score decreases with increasing lead time. Skill for the MAM season is lower (ROC-AUC = 0.66 at Lead 0, negligible at longer leads). The higher skill of the OND season compared to the MAM season can be explained by the stronger influence of large-scale climatic oscillations (e.g. ENSO) in the OND season compared to the MAM season (see Section 2.2). Clear spatial differences in forecast skill can be observed (Fig. A.2). Generally, forecast skill is considerably lower in Ethiopia than in other areas. Kenya and Somalia show high skill (ROC-AUC > 0.7) for the OND season, even for Lead 1 forecasts (Fig. A.2). Among all of the countries under observation, the highest skill is observed in Somalia for the OND season.

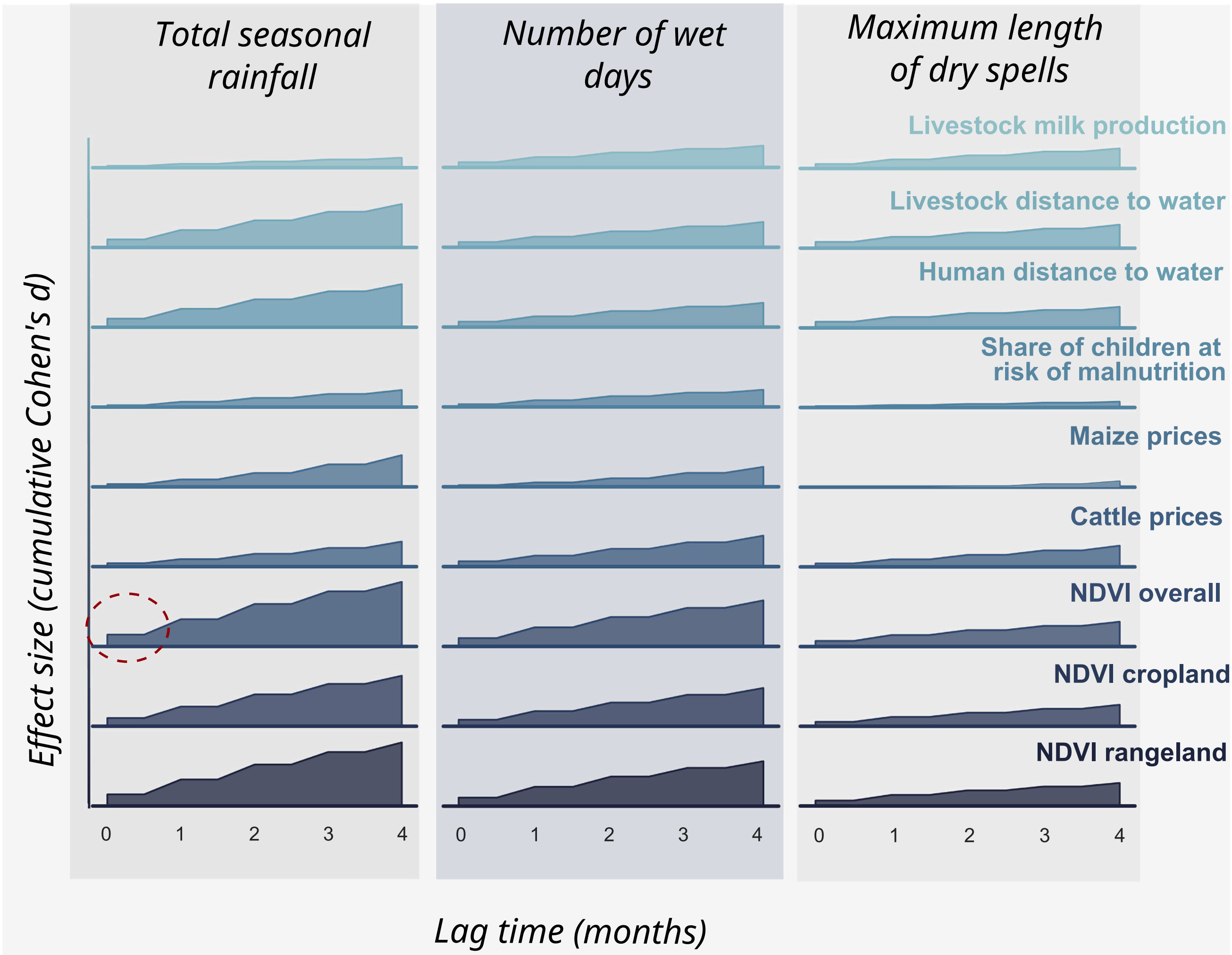

Fig. 4. The effect of meteorological droughts (<0.3th quantile) extracted from the three different rainfall indicators (the total seasonal rainfall, the number of wet days and the maximum length of dry spells) during the MAM and OND seasons on accumulated drought impacts as measured by the effect size d_s. Lag time represents the delay in number of months after the rainy seasons that is used to calculate three-monthly mean impacts (e.g. lag 1 = the April–May-June and November–December-January periods). The red circle serves to highlight a drought indicator (NDVI) which has a quick response on rainfall deficits.

These results in forecast skill can be translated to the value of the forecasts in the PEV analysis. The low predictability of MAM rainfall results in low forecast values for triggering early action (Fig. 5, top). Decisions triggered for the MAM season for leads higher than zero result in neglectable economic value. Forecasts for the OND season have considerable value for many users, which remains even for longer leads (Lead 1 and 2; Fig. 5). These PEV values, as well as the optimal probability triggers (P_t) vary for different decision-makers which trigger actions with varying cost-loss ratios (C/L; Fig. 5). Fig. 5 shows that the highest PEV (PEV_{max}) is obtained with a C/L ratio that is equal to the climatological frequency of the event, which in this case is 0.33 (Richardson, 2000). It also shows that in order to maximise the value of the forecasts, users with low C/L ratios (i.e. actions that are cheap relative to the preventable damage from the event) should act relatively often, with a low P_t (e.g. 10 %, red line). For example, an action with a C/L = 0.15 should be triggered by the 10 % probability threshold when triggered for the OND season at Lead 0. For users with high C/L ratios, it is often more beneficial to trigger action only when certainty in the forecast is higher, using high probability thresholds. Actions with a very low or high C/L ratio have zero or negative value and should thus never be triggered, as it is more beneficial to always and never trigger action, respectively.

We calculated and displayed the maximum PEV (PEV_{max}) of action over the range of C/L ratios on a pixel-level. For Lead 0, early action in the whole HoA region has considerable value for the OND season, with a PEV_{max} of 0.43 on average (Fig. 6, bottom). In most of the region the possibility of extracting substantial value from OND forecasts remain present also at Lead 1 and 2, except for most of Ethiopia. The high OND forecast skill (see Fig. A.2) for Somalia translates into high PEV_{max} values for early action, especially for Lead 0. Across Somalia PEV_{max} is 0.54 on average, but high PEV_{max} values close to 0.8 are found in the centre of the country. Overall, the MAM season has low PEV_{max} values, implying that the usefulness of the SEAS5 seasonal forecasts is limited. A clear exception is Kenya at Lead 0, where MAM forecast value is considerable (PEV_{max} = 0.39).

4.3. Anticipatory action on drought forecasts: an illustrative case study

In the previous sections, we outlined the value of the SEAS5 forecasts for anticipatory action in the HoA. In this section, we demonstrate how these scientific results can be used in practice by a forecast user in the region. For a given cost-loss ratio of actions the optimal probability that should trigger action can be derived. This cost-loss ratio is context specific. For illustration, we showcase a hypothetical situation involving an agro-pastoralist in Kenya.

Droughts heavily impact the livestock sector in Kenya. Millions of

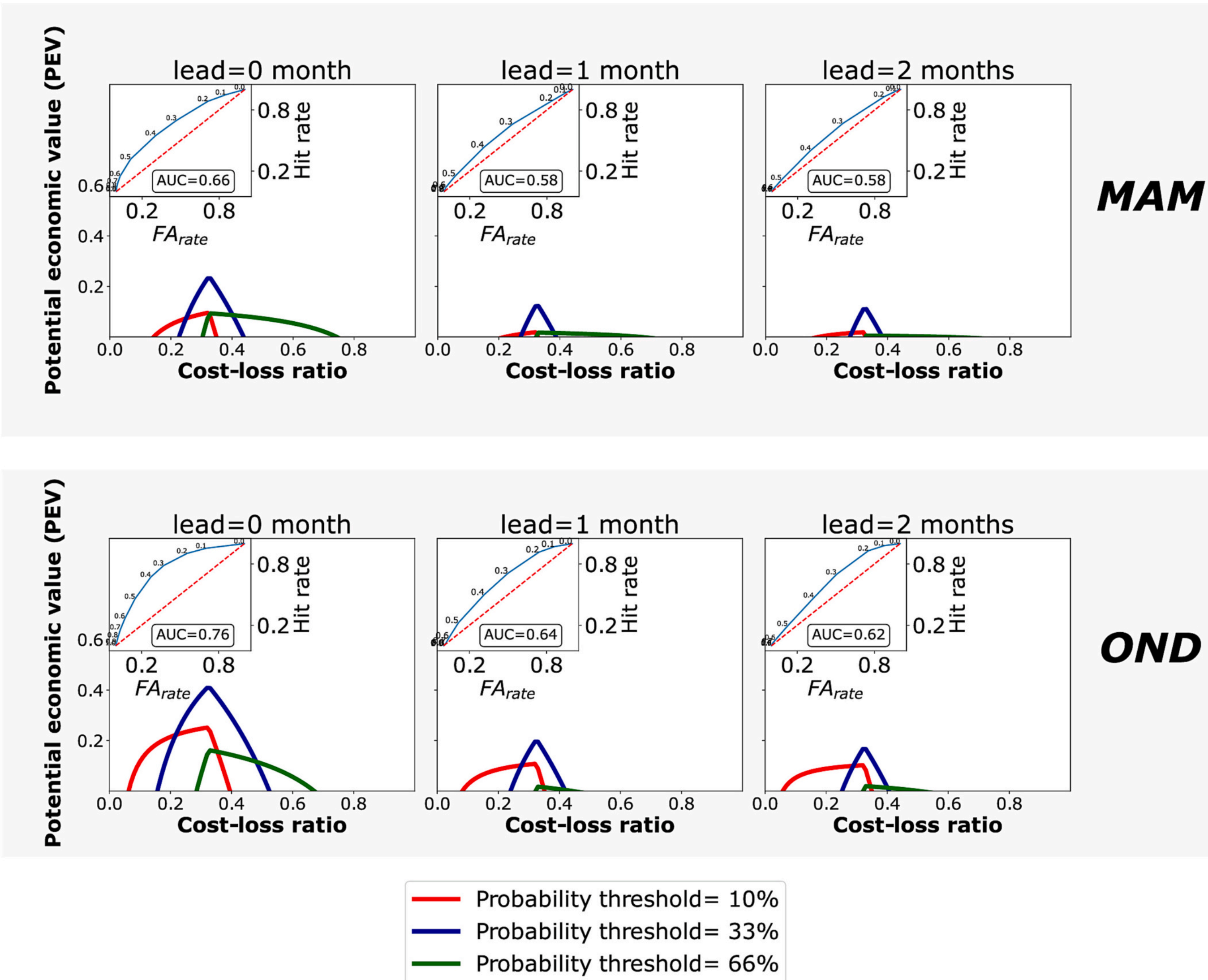

Fig. 5. The economic value (PEV) for ECMWF SEAS5 lower-tercile rainfall forecasts for the MAM season (top) and the OND season (bottom) averaged over the HoA region, with lead times of zero, one and two months. Different probability thresholds (10 %, 33 % and 66 %) to trigger action are displayed. The C/L ratio can be derived from the action costs C and preventable damage L. The top left of each graph displays the forecast skill with ROC curves (including ROC-AUC skill scores).

animals have died in the current drought. The government of Kenya allocates substantial funding on drought-intervention measures, most of which target the livestock sector (NDMA; Government of Kenya, 2021). A coping mechanism during droughts is the reduction of herd sizes (i.e. destocking). It injects income into the local economy and it may keep the remaining animals alive (FAO, 2018a, 2018b; Government of Kenya, 2012). However, the price of cattle falls during droughts as a result of the deteriorating condition of the livestock and of market dynamics (see Section 4.1). Therefore, emergency destocking during droughts has previously been evaluated negatively (Watson and van Binsbergen, 2008). Hence, the International Livestock Institute suggests to implement early livestock destocking triggered by early warnings, before animals weaken and their prices fall (Watson and van Binsbergen, 2008).

We evaluate the hypothetical performance of early destocking decisions triggered by SEAS5 drought early warnings. We evaluate the decision of a pastoralist to sell one tropical cattle unit (TCU). The benefit of this action is the extra income that is generated by the higher market value of one TCU, compared to its value during or after a drought. In the cost-loss framework, this benefit is equal to the avoidable loss (L_p, see Table 1), consisting of the market value decrease. From the NDMA impact data (see Section 4.1) we estimated this avoidable loss to be 2964KSH/TCU. We assumed the unavoidable losses L_u to be equal to zero: no livestock mortality or destocking during drought is necessary if early action is taken. The costs that are associated with this action consist of missed milk production. However, these action costs are not fixed: in the case of a drought, the volume of production that is forgone is lower than in no-drought seasons. We estimate missed milk production from the NDMA impact data under drought conditions to be 4 L/TCU and no-drought conditions at 4.5 L/TCU per month. For an average milk price of 65 KSH/L (Government of Kenya, 2021) this leads to the expected revenue from milk production conditional on the drought occurrence.

We assume that pastoralists can estimate the period over which their cattle can survive in both drought and no-drought conditions. Differences in lifetime influence the missed milk production and thus the revenue for the pastoralist. Pastoralists normally only destock weak livestock, but they could also destock stronger livestock if the drought is severe. Therefore, we develop three scenarios for the pastoralist: 1) selling weak livestock, 2) selling normal livestock and 3) selling strong livestock. We define weak livestock as livestock that would survive for one month under drought conditions and for six months under normal

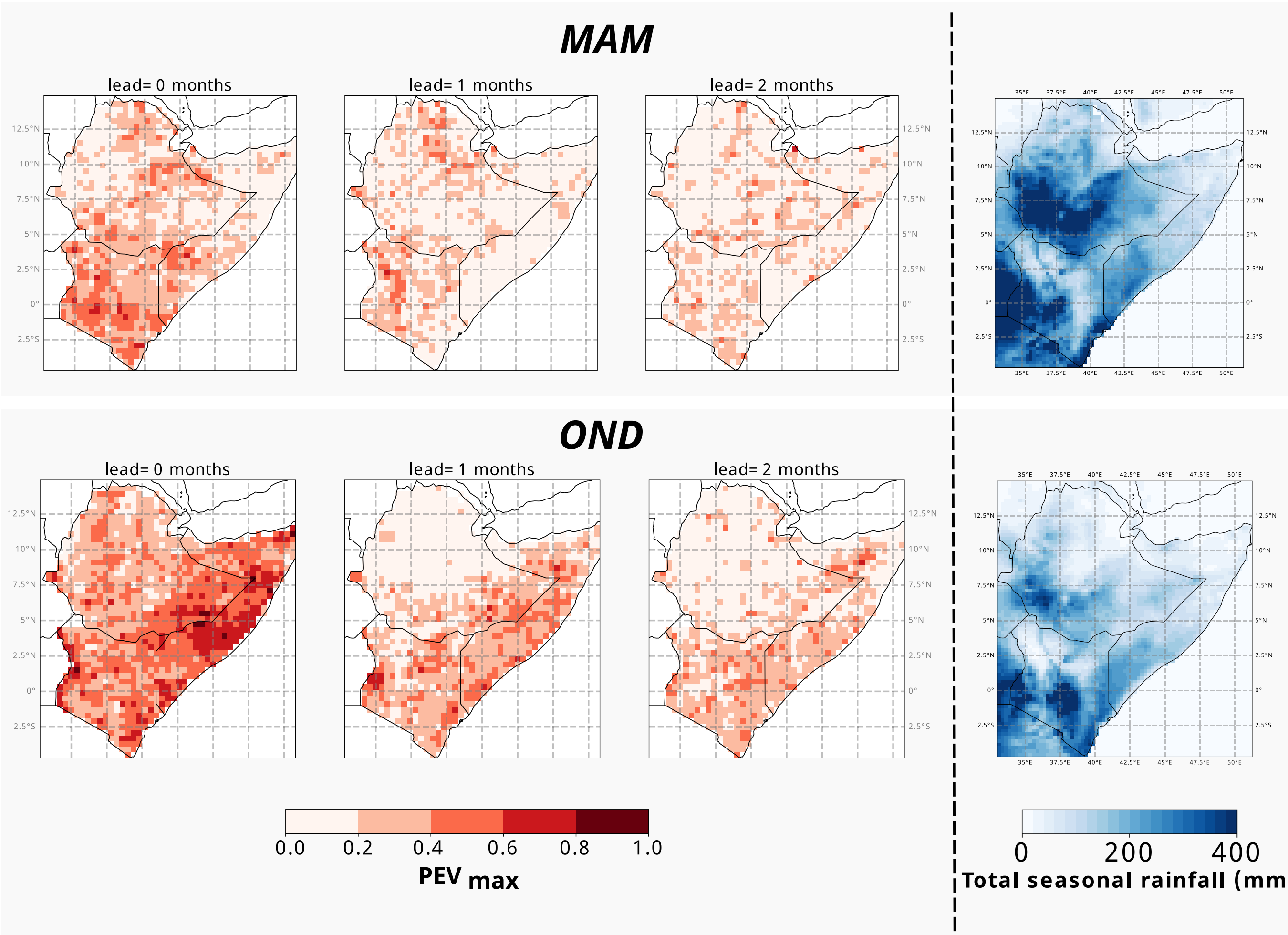

Fig. 6. Maximum potential economic value (PEV_{max}) for SEAS5 lower-tercile rainfall forecasts for the MAM (top) and OND (bottom) rainy seasons for three different lead times (Lead 0, Lead 1 and Lead 2). Right column shows long-term rainfall climatology, as presented in Fig. 1 (top), for reference.

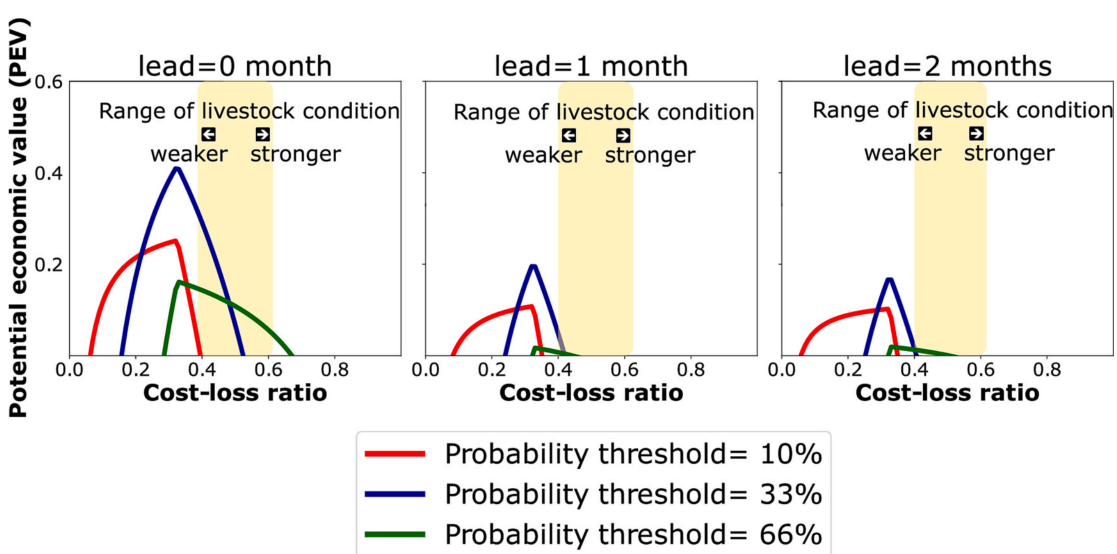

Fig. 7. Potential economic value for destocking as an early action for the OND rainy season in Kenya, triggered on the first day of the season (Lead 0), one month ahead of the season (Lead 1) and two months ahead of the season (Lead 2). The yellow boxes indicate the C/L ratios that were found for a pastoralist in Kenya who is considering destocking, which vary based on the local context (e.g. the condition of the cattle at the time of destocking).

conditions. Normal livestock is assumed to survive for three months in a drought and for 12 months if there is no drought. Strong livestock is only marginally affected and survives for 16 months if there is a drought and for 24 months otherwise. The survival rates of weak and normal livestock are based on the relatively high livestock mortality rates that are common for Kenyan pastoralists during droughts (e.g. 14–43 % in 2005/2006 and 60 % in 2008/2009, respectively; Nkedianye et al., 2011; Zwaagstra et al., 2010).

We subsequently calculate the C/L ratios for weak, normal and strong livestock. We calculate the C/L ratios by using the expenses E_{11}, E_{12}, E_{21} and E_{22} for each scenario that is given in Table 1 (see Section 5 in Richardson, 2003). We found a C/L ratio of 0.39 for sales of weak livestock. For normal livestock this increases to 0.61 due to the higher action costs (i.e. missed milk production over a longer period). Selling strong livestock results in a C/L ratio in excess of 1, so selling these animals is never profitable.

Translating this to early-action, we found that the use of SEAS5 drought forecasts for herd size management ahead of the OND season can be economically valuable (Fig. 7). PEV is substantial at Lead 0, and higher for weaker livestock conditions. Destocking some months ahead of the season (Lead 1 and 2) has low value. It follows that livestock can be destocked at the first day of the season (Lead 0), with the optimal probability trigger thresholds being 33 % for weak livestock, and 66 % for stronger livestock. Stronger cattle conditions require higher probability trigger thresholds (P_t) to give meaningful PEV values. In other words, a pastoralist needs to have more certainty in the drought forecast for triggering destocking for stronger livestock, because the action costs are higher. Lower trigger thresholds have no considerable value.

These conclusions cannot be generalised for all pastoralists because local conditions and characteristics may vary. We used the region-wide PEV curves (Fig. 5) for this destocking intervention at a point-scale. The region-wide PEV curves shown in Fig. 5 are comparable for Kenya. We therefore used these graphs in this example. However, some regions showed much lower PEV values (such as large parts of Ethiopia, Fig. 6), and thus forecast users in these regions cannot directly use the results presented in Fig. 5. Pastoralists can derive an individualized probability threshold by calculating their own action costs and preventable losses. We assumed the only difference between weak and strong livestock is their lifetime, and therefore the missed milk production when destocking. However, livestock conditions influence a broader range of factors. For example, weaker livestock probably has a lower milk production rate, requires more medical costs and has a lower market value decrease during drought. These are all factors that a pastoralist can take into account when planning an early destocking intervention.

5. Discussion

5.1. Rainfall product accuracy

Although CHIRPS is widely accepted as an accurate rainfall product in East Africa, rainfall estimates from satellite sensors still exhibit systematic and random biases. This applies, in particular, to orographic rainfall of the kind that is observed in the Mount Kenya region and in the Ethiopian Highlands (Dinku et al., 2007; Kimani et al., 2017; Seregina et al., 2019). Kimani et al. (2017) showed that, although it exhibits some negative bias, CHIRPS performs remarkably well in detecting this orographic rainfall, which can be attributed to the inclusion of rain gauges and microwave sensors from the Tropical Rainfall Measurement Mission used for calibration.

The accuracy of CHIRPS rainfall estimates over the arid lands in the region is more concerning. Both the rain gauges that are included in CHIRPS and the independent validation stations are not spatially uniform across East Africa, with low coverage over the drylands (Dinku et al., 2018, Fig. 1). Moreover, there is a large decline in the number of ground stations in Kenya, Ethiopia and Tanzania over the last decades (see Fig. 3 in Dinku et al., 2018). Nonetheless, the CHIRPS dataset is generally perceived as one of the most accurate rainfall datasets for the continent, including East Africa (Kimani et al., 2017; Maidment et al., 2017) and its drylands (Macharia et al., 2020). We also tested the TAMSAT rainfall dataset in our study, which shows similar accuracy compared to CHIRPS across five countries in Africa (Maidment et al., 2017). This gave similar results in our drought impact and PEV analyses (not shown).

5.2. Drought impact analysis

We used on-the-ground data from the NDMA in order to understand the development of the impacts of meteorological drought better (Section 4.1). To the best of our knowledge, using these direct on-the-ground indicators is a novel approach. The NDMA drought impacts are gathered from sentinel sites, where officials observe drought conditions monthly. This process can be inaccurate, especially in respect to indicators which are hard to measure, such as walking distance to water. However, the availability of nine years of monthly on-the-ground socio-economic drought indicators is a unique feature, and such data is seldom available for other African countries.

We tested monthly impact developments triggered by monthly rainfall deficits, but we found a smaller effect on impacts than for seasonal rainfall deficits. Our impact analysis (Section 4.1) showed that seasonal variability alone is not an accurate predictor of malnutrition. This result is in line with the findings that are reported in other studies. Coughlan de Perez et al. (2019) found that a longer accumulation time of rainfall deficits (12 months) greatly increase the likelihood of food insecurity and famine in pastoral regions. Therefore, future studies are needed to explore how these multi-season drought indicators can result in improved food security forecasting and early-action triggers.

Although seasonal rainfall totals proved to be influential, this obviously is not the only feature that determines impacts. Some environmental impact indicators, such as NDVI and walking distance to water sources, have a stronger connection to rainfall than more indirect indicators, such as malnutrition. Moreover, external factors, such as conflict, land and resource management, and national and regional governance can all erode the capacity of communities to adapt and cope (FAO, 2018a). For example, in Kenya, the 2008–2011 drought was preceded by the heavy post-election violence and unrest that followed the 2008 elections, which caused fuel and food prices to skyrocket (Government of Kenya, 2012). Recent international crises, such as the COVID-19 pandemic and the Ukrainian conflict, have caused trade blockades, which have also impacted communities in East Africa.

5.3. The use of SEAS5 forecasts to trigger early action

We verified the ECWMF forecasts for the MAM and OND seasons, which are the most important rainfall seasons in the HoA region. However, for some subregions substantial rainfall occurs in other seasons (Seregina et al., 2019). For instance, the Ethiopian Highlands and south-western Kenya receive more consistent rainfall during the June–July-August-September season (MacLeod, 2019). Some have argued that the MAM season should not be defined as a single rainy season because each month has different characteristics and is associated with different causal factors and teleconnections (e.g. Nicholson, 2017). Nevertheless, we retained the MAM and OND seasons as our main rainfall seasons, mainly to maintain consistency with operational forecasts (e.g. the GHACOF climate outlooks) and because this approach is employed in most contributions to this domain.

We adopted the 33rd percentile (i.e. lower tercile) as our threshold for defining meteorological droughts from the CHIRPS and SEAS5 climatology, separately. This means that an automatic correction for systematic errors is in place for both the forecast verification (ROC-AUC score) and the early-action analysis, which are based on the lower terciles. No additional post-processing was applied to optimise reusability of operational ECMWF model runs. More extreme events (e.g. the 10th percentile) generate higher impacts (see Fig. 3), but limit the sample size of drought occurrences disabling robust verification of forecasts and early-action analyses. Therefore, we did not use these lower thresholds for these analyses.

The OND season is relatively predictable due to the large influence of the IOD and the ENSO. However, the influence of these large-scale teleconnections on East African rainfall is non-stationary and subject to large regime shifts (Manatsa et al., 2012; Nicholson, 2015). We found that, as far as Kenya and Somalia are concerned, skill in the SEAS5 forecast is more persistent over lead time when verified over the 2000–2020 period than when verified over the current period. While comparable skill was found for Lead 0, skill is higher for longer leads when verified only for the 2000–2020 period. This increases average PEV_{max} by around 0.1 for both southern Somalia and Kenya on all leads except 0. Notably, this increase in SEAS5 forecast skill for longer leads was not found for the MAM season. Climate regime shifts may explain this difference. The most recent shift occurred in 1997, after which the influence of the ENSO and the IOD on East African rainfall increased (Nicholson, 2015). This might have contributed to a higher ECMWF SEAS5 skill in the current climate regime. Despite the non-stationarity of the drivers of precipitation, we still assume that the 1981–2020 period reflects the performance of the SEAS5 forecasts most accurately because the larger number of drought events increases the robustness of the forecast verification. The period is in accordance with other ECMWF verification studies that concern the region (MacLeod, 2018, 2019).

We showed that SEAS5 forecasts are valuable for decision-making in the MAM and OND seasons, in particular in respect of the latter. PEV curves (Fig. 5) can be used to decide if and when to trigger action. This depends on the cost-loss ratio of the action that is considered, but also on the risk preferences of the users. Risk-averse decisions are taken at lower P_t thresholds and thus are induced more frequently, which reduces the long-term event losses, but leads to higher long-term costs (Richardson, 2003). To finetune risk preference profiles, weights can be assigned to the various cost-loss variables accordingly.

We investigated destocking as a pastoral early-action strategy. Normal destocking, during drought, can be seen as a coping mechanism. Herders are often emotionally connected to their herds, and destocking may be a last resort rather than a form of early action. Alternative adaptation strategies exist that can generate higher cost-benefit ratios. It has been reported by Bekele and Abera (2008) that emergency livestock-feed supplements yield a cost-benefit ratio of 1.9 to 1.6 in Ethiopia. Actions of this kind, including the initiatives of the IFRC, the World Food Programme (WFP) and the FAO can be tested in a PEV analyses of the kind that was presented here. Given the high value for Lead-0 forecasts and the rapid decrease of value for longer leads (Fig. 5), the value of sub-seasonal forecasts can be explored further in future studies.

6. Conclusions and recommendations

This study has shown that the ECMWF SEAS5 forecasts add substantial value to decision-making for the management of droughts in the HoA. We used the PEV theory to determine the value of these forecasts in three different countries (Kenya, Ethiopia and Somalia) for the MAM and OND rainy seasons. We found high values for triggering action before the OND season, especially in Kenya and Somalia (PEV_{max} of 0.45 and 0.54, respectively). The forecasts are found to be highly valuable for Somalia, especially in the central region of the country ($PEV_{max} > 0.7$). The MAM season is less predictable, which translates into low value across all lead times (PEV_{max} of 0.26). Kenya, which showed considerable value at Lead 0 for the MAM season, is an exception. We found that the forecasts have a low value for large parts of Ethiopia, except for the OND season at Lead 0.

We arrived at these results by applying a forecast verification on 40 years of ECMWF SEAS5 hindcasts, with CHIRPS rainfall data as ground truth. We defined meteorological drought as total rainfall <33rd percentile (i.e. lower tercile) of the seasonal climatology. We analysed on-the-ground drought-impact data from 21 different counties in Kenya to show that this rainfall indicator results in major drought impacts, larger than the number of wet days or the maximum length of dry spells. We found that the mean impact in MAM and OND meteorological droughts are always higher than for no-drought seasons, with six of the nine indicators showing a large effect (as classified by Cohen's *d*). It follows that total seasonal precipitation forecasts, being impact-based forecasts of droughts, are often appropriate triggers for meaningful early actions in the region.

The strength of the PEV analysis is that a forecast user only needs to determine their cost-loss ratio to optimise action triggers and the value of early action. We showed that actions with lower (higher) C/L ratios should be triggered by lower (higher) probability thresholds. We illustrated how a forecast user may determine their cost-loss ratio in practice by reference to an illustrative example of a pastoralist considering whether to destock livestock ahead of the season. This hypothetical result underlines that the optimal action triggers and expected long-term values are as important for end users as the forecasts themselves, and that they should be disseminated accordingly. Inappropriate or arbitrary choices of probability trigger thresholds can lead to lower forecast values and can even lead to additional damages (i.e. negative PEV values).

Future early action guidelines and policies of local governments and NGOs (e.g. WFP, FAO and the IFRC) can be extended with concrete early action triggers for specific regions and users. These policies and guidelines should include concrete recommendations for early action which can be adopted in national and local policies (e.g. in the early-warning bulletins from the NDMA in Kenya). Moreover, regional climate centres, such as ICPAC, could employ the PEV analysis to translate their forecasts into early action triggers. When this translation is well configured, it can support the design of early action triggers for specific sectors and users at the GHACOF, a key event at which forecasts for the next season are released. Besides the ICPAC forecasts, future research should investigate other forecast types and their ability to trigger action, such as soil moisture forecasts (e.g. from FEWS-NET Land Data Assimilation System, FLDAS) and sub-seasonal forecasts. For local communities, mobile apps or SMS/USSD services can allow users to input cost-loss ratios and obtain advices to trigger action together with their expected economic benefits. Therefore, future advances in mobile technology should focus not only on the dissemination of forecasts but also on the means by which users can set optimal triggers.

CRediT authorship contribution statement

Tim Busker: Conceptualization, Formal analysis, Methodology, Software, Writing – original draft, Writing – review & editing, Visualization. **Hans de Moel:** Conceptualization, Supervision, Methodology, Writing – review & editing. **Bart van den Hurk:** Conceptualization, Supervision, Methodology, Writing – review & editing. **Jeroen C.J.H. Aerts:** Conceptualization, Supervision, Writing – review & editing, Resources, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A

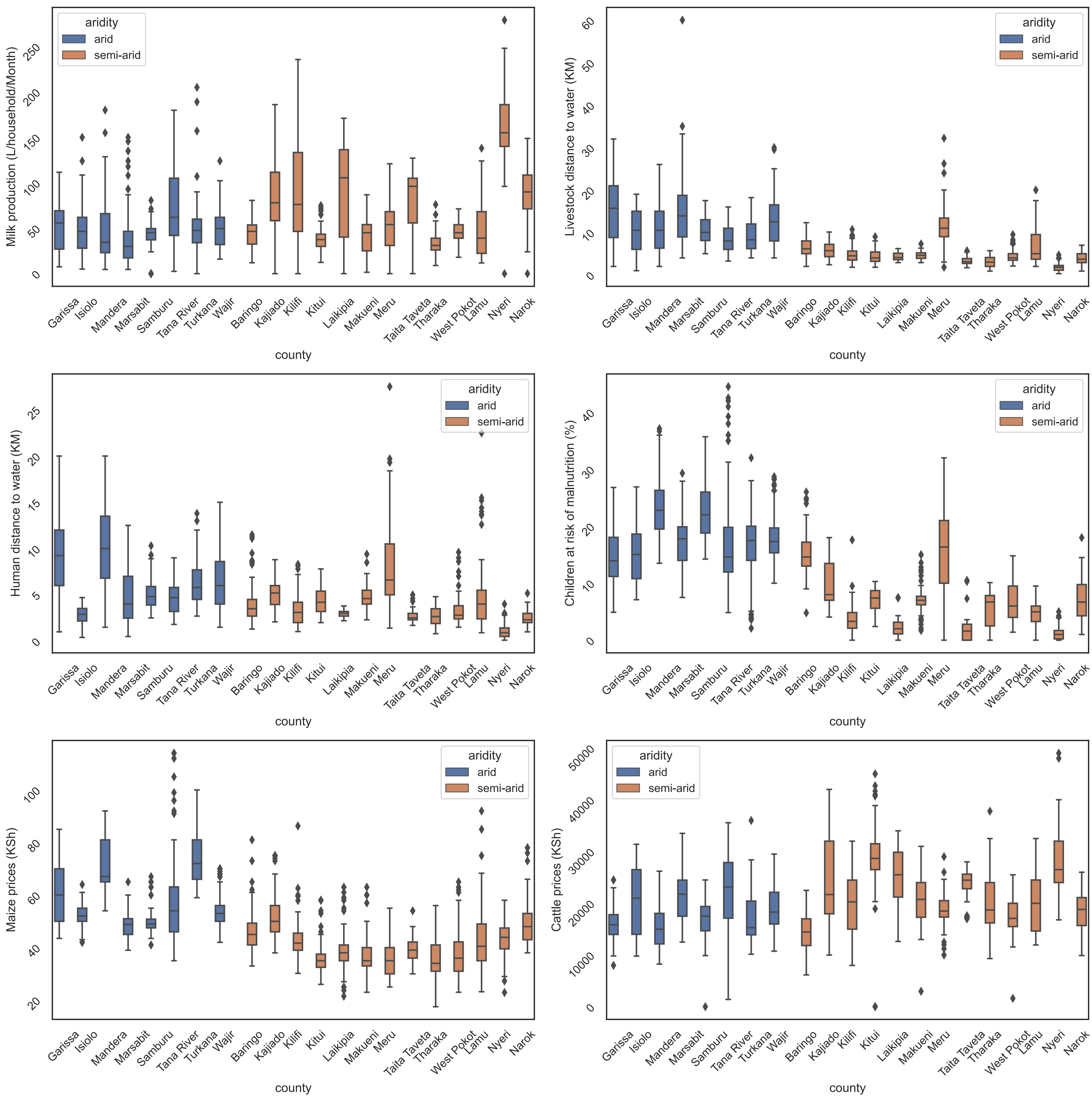

Fig. A.1. On-the-ground drought-impact indicators from NDMA, gathered over 21 arid and semi arid counties in Kenya during monthly surveillance of drought conditions over the 2013–2021 period. The spreads in the boxes for each county indicate monthly impact variability per county.

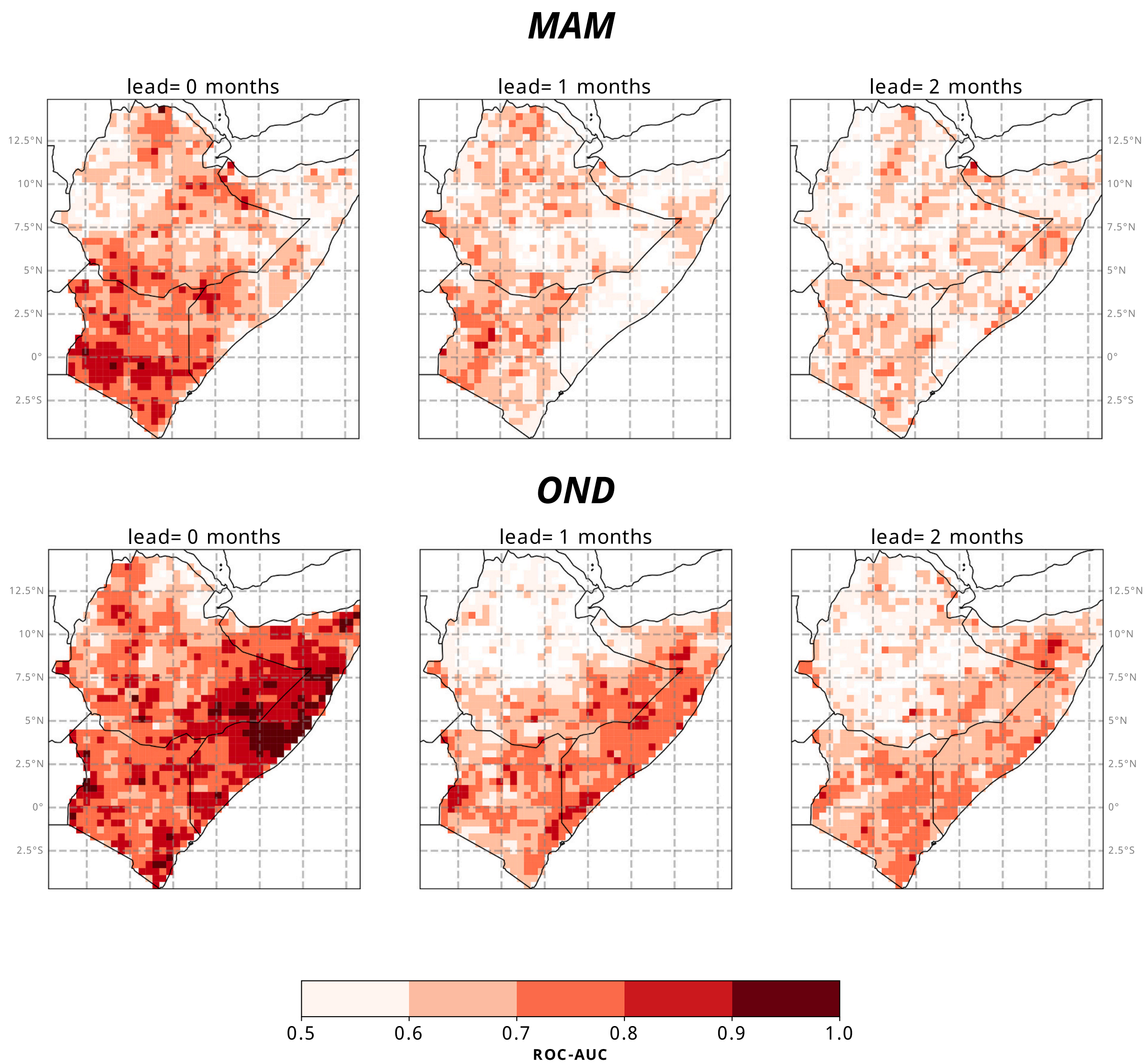

Fig. A.2. ROC-AUC scores for seasonal droughts (seasonal total rainfall <33rd percentile) predicted by ECMWF SEAS5, for multiple lead times ahead of the MAM (top) and OND (bottom) season. Lead 0 refers to the first day of the respective season. Every score >0.5 (orange-red colours) is skillful (i.e. better than a random forecast).

Table A.3
The Cohen's d effect sizes of seasonal meteorological droughts (<0.3th quantile) on the generation of drought impacts, using three different rainfall indicators (seasonal totals, number of wet days and maximum dry spell length), different lag times and the nine drought impact indicators. Colors are for visualization purposes only, and serve to illustrate the magnitude of the values found from low (light blue) to high (dark blue).

	Seasonal rainfall totals						Seasonal number of wet days						Seasonal maximum dry spell length					
Lag times	0	1	2	3	4	Average	0	1	2	3	4	Average	0	1	2	3	4	Average
Catte prices	0,32	0,40	0,50	0,55	0,60	0,48	0,50	0,54	0,65	0,62	0,63	0,59	0,34	0,38	0,43	0,43	0,45	0,41
Human distance to water	0,81	0,93	0,89	0,76	0,68	0,82	0,52	0,51	0,49	0,42	0,37	0,46	0,57	0,45	0,36	0,31	0,31	0,40
Livestock distance to water	0,76	0,90	0,91	0,83	0,72	0,82	0,49	0,52	0,50	0,47	0,42	0,48	0,60	0,47	0,40	0,37	0,38	0,45
Livestock Milk production	0,17	0,20	0,22	0,20	0,17	0,19	0,49	0,47	0,43	0,36	0,30	0,41	0,43	0,43	0,38	0,36	0,31	0,38
Maize prices	0,26	0,45	0,62	0,80	0,87	0,60	0,15	0,26	0,40	0,52	0,57	0,38	-0,08	-0,05	0,09	0,20	0,27	0,09
Share of children at risk of malnutrition	0,17	0,32	0,37	0,38	0,38	0,32	0,27	0,38	0,39	0,34	0,27	0,33	0,13	0,11	0,12	0,11	0,11	0,12
Total area NDVI	1,12	1,45	1,43	1,19	0,90	1,22	0,80	1,02	0,97	0,86	0,70	0,87	0,54	0,57	0,46	0,40	0,39	0,47
Cropland NDVI	0,78	1,09	1,14	1,00	0,78	0,96	0,63	0,81	0,80	0,74	0,64	0,72	0,42	0,47	0,40	0,37	0,39	0,41
Rangeland NDVI	1,10	1,41	1,41	1,19	0,90	1,20	0,80	1,03	0,96	0,82	0,63	0,85	0,52	0,54	0,43	0,37	0,35	0,44
Average	0,61	0,79	0,83	0,77	0,67	0,73	0,52	0,61	0,62	0,57	0,50	0,57	0,38	0,38	0,34	0,32	0,33	0,35

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