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The potential value of seasonal drought forecasts in the context of climate change: A case study of the African elephant conservation sector

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Abstract

This study investigates meteorological drought in sub-Saharan Africa within the context of elephant conservation. Prolonged drought significantly impacts elephants, leading to increased mortality rates and heightened human–elephant conflicts. We assess both the anticipated 21st century changes in impact-relevant meteorological drought metrics and the efficacy of existing forecasting systems in predicting such droughts on seasonal time scales. The climate change element of our study uses the 6th Coupled Model Intercomparison Project (CMIP6) ensemble to evaluate projected change in 3-month Standardized Precipitation Index (SPI3). We then carry out a quantitative assessment of seasonal forecast skill, utilizing 110 years of precipitation hindcasts generated by the European Centre for Medium Range Forecasting (ECMWF) system. Our findings indicate that persistent drought is projected to become more frequent over the 21st century in southern Africa, where the majority of elephants reside. Analysis of seasonal hindcasts indicates that, while the forecasts have greater skill than climatology, they remain highly uncertain. Previous work suggests that it may be possible to reduce this uncertainty by contextualizing forecasts within specific climate regimes. However, even with improved forecast skill, effective action hinges on the alignment of forecasts with the practical needs of conservation practitioners. Over the next decades, a co-production approach will be critical for leveraging seasonal forecasts for climate change adaptation within the conservation sector.

KEYWORDS

Africa, climate change impacts, droughts, ecology, elephants, forecasting, hazards, projections, resilience, seasonal

1 | INTRODUCTION

Effective early warning reduces the economic and social cost of natural disasters, and hence their disproportionate impact on vulnerable communities. Indeed, analysis conducted by the Global Commission on Adaptation estimates that investing $800 million in early warning systems in developing countries would prevent losses of $3–16 billion per annum (WMO, 2022). The ability to anticipate hazards is critical to early warning systems (UNDRR, 2019; UNISDR, 2015). Robust, reliable and actionable meteorological forecasts are thus a key part of mitigating weather-related disaster. On short time scales, issuing warnings ahead of tropical cyclone landfall, for instance, if communicated effectively can facilitate evacuation, reducing the death toll of such events. For example, advance warning of 2013 tropical storm Mahasen in Bangladesh enabled ~1 million people to be evacuated. On longer timescales, provided they are integrated into effective management strategies, seasonal forecasts of drought indicators enable decision-makers to prepare, for example, by encouraging the cultivation of drought resistant crop varieties (Andersson et al. 2020; Tadesse et al., 2008). In severe cases, warnings of persistent and severe drought can inform the mobilisation of humanitarian aid, for example, via the Red Cross Disaster Response Emergency Fund (DREF) (Braman et al., 2013). Forecasts are not just useful for disaster management. Indeed, a number of decision support tools have been developed that enable stakeholders to utilise long and short term forecasts in their routine decision-making—improving resilience to variability in the weather (Black et al., 2023). It follows from the previous discussion that robust systems for early warning are key to adapting to a climate in which drought is more common. This is especially true in Africa, where drought is already a common and devastating occurrence (Ahmadalipour & Moradkhani, 2018; Masih et al., 2014).

Over the next century, although northern and equatorial Africa is projected to get wetter, the south of the continent is projected to dry significantly (Almazroui et al., 2020), raising the question of how robust early warning systems may build resilience to climate variability in a future, more hostile climate. In this context, future change in variability goes beyond interannual variation in annual mean temperature and precipitation to encompass projected change in seasonality, drought and soil moisture (Berg & Sheffield, 2018; Dunning et al., 2018).

Most work on early warning of drought has focused on impacts in the agricultural sector (Winsemius et al., 2014). This study builds on this work by considering the role of early warning in mitigating climate change impacts on wildlife conservation, and in particular on the management of African savannah elephant (*Loxodonta africana*) populations.

Climate change is set to become a major driver of global biodiversity loss within the 21st century (Urban, 2015), and associated changes in the frequency of extreme weather events, including drought, may drive local extinctions at more immediate timeframes (Harris et al., 2018). In sub-Saharan Africa, wildlife populations provide an important draw for foreign exchange through nature-based tourism. The wildlife tourism industry (including consumptive and non-consumptive activities) accounted for more than 7% of sub-Saharan Africa's GDP in 2016 and employed 6% of the population, providing more than 15 million jobs (Price, 2017).

Drought increases mortality rates of elephant populations and can have life-long implications for reproductive success (Dudley et al., 2001; Foley et al., 2008; Lee et al., 2022; Okello et al., 2016; Wato et al., 2016). Reduced elephant densities correlate with lower tourist visitation rates in parks across sub-Saharan Africa (Naidoo et al., 2016), and drought conditions were found to reduce tourism in South Africa (Mathivha et al., 2017). It follows therefore, that drought both directly and indirectly reduces tourism revenues with important implications for socio-economic development. Further, elephants act as crucial ecosystem engineers, providing multidimensional services and benefits to nature and society (van de Water et al., 2022), so their loss can negatively affect ecosystem resilience to climate change and coping strategies of local communities.

It is logical to assume that forecasts enable anticipatory action, and hence improve the resilience of many sectors, including the conservation sector, to climate related shocks, including severe drought. Regional centres now routinely release seasonal forecasts of precipitation, temperature and related metrics, such as the standardised precipitation index (SPI). These forecasts contribute to more holistic drought early warning systems (DEWS) (Funk et al., 2019; van Ginkel & Biradar, 2021). However, despite the multidimensional benefits provided by biodiversity and the obvious threats posed by extreme weather and climate change, there has to date, been limited use of seasonal forecasts in guiding conservation decision-making (Tulloch et al., 2020). The growth of near-term ecological forecasting presents promise (Dietze et al., 2018) but few operational and actionable early warning systems exist (Boult, 2023). The reasons for this may include a lack of capacity among conservation practitioners to utilise highly uncertain meteorological forecast data in decision-making, added uncertainty in the effectiveness of conservation actions and a lack of useful skill in forecasts (Dietze et al., 2018).

This study considers the last of these issues through a skill assessment of a relevant metric of drought.

In this article, we reflect both on changing drought risk in regions populated by elephants and how advances in climate science and coproduction approaches have the potential to maximise the usefulness of forecasts for biodiversity conservation. The remainder of the article is structured as follows: The methodology and datasets are introduced in Section 2. Section 3 presents an assessment of projected change in drought occurrence in regions of eastern and southern Africa currently inhabited by elephants, together with a brief analysis of our current skill in forecasting such events on seasonal time scales. The article concludes with a few reflections about the potential utility of seasonal forecasts for adaptation to climate change by the conservation sector.

2 | METHODS AND DATA

Our study has two strands: a survey of projected change in drought over the 21st century, based on the 6th Coupled Model Intercomparison Project (CMIP6) model output, and a brief analysis of the skill and utility of the current seasonal forecasts. Throughout, the analysis is conducted through the lens of elephant conservation, by considering metrics to which elephants are particularly sensitive, and by masking datasets on regions known to be currently inhabited by elephants.

2.1 | Data

2.1.1 | CMIP6 output

This study is based on output from an ensemble of 38 models from CMIP6. Further details about the models used can be found in Table S1 and an overview of CMIP6 is presented in Eyring et al. (2016). To avoid biasing the multi-model means towards any particular model, a single ensemble member for each model is used (r1i1f1, where available). The study compares two shared socio-economic pathways: SSP 2–4.5 and SSP 5–8.5. Under SSP 2–4.5, emissions stabilise by the middle of the 21st century and then decline; under SSP 5–8.5 emissions do not stabilise until the end of the 21st century. Data from the CMIP6 ensemble were extracted for 1850–2100, with historical model integrations (CMIP Historical) spliced together with projections from 2015 onwards (ScenarioMIP). To assess climate change, a 2060–2090 time slice was compared against the 1960–1990 baseline period. Thirty-year periods were used to account for the interdecadal variability that characterises African precipitation.

For this study, monthly precipitation (standard CMIP6 variable name pr) was analysed. Monthly data were extracted from the BADC or DKRZ ESGB gateways (http://esgf-index1.ceda.ac.uk or http://esgfdata.dkrz.de), and the data were re-gridded to a common 1° grid. The re-gridded data used in this study have been permanently archived at https://gws-access.jasmin.ac.uk/public/tamsat/cmip_drought_data/.

2.1.2 | Seasonal hindcasts

The seasonal hindcast data used in this study are the Coupled Seasonal Forecasts of the 20th Century (CSF-20C)—described fully in Weisheimer et al. (2020). The CSF-20C comprise 110 years of ensemble hindcasts (1900–2010), initiated on 1 February, 1 May, 1 August and 1 November and run for four forecast months. The February and May start date hindcasts consist of 25 ensemble members and the August and November start date hindcasts consist of 51 ensemble members. The hindcasts are produced using the European Centre for Medium Range Weather Forecasting (ECMWF) Integrated Forecasting System (IFS) coupled model version cycle 41r1, which is similar to the current ECMWF seasonal forecasting system (SEAS5). The native horizontal resolution of the atmospheric data is T255 (~80 km). For the purposes of this study, the data are re-gridded to the same 1° grid used for the projections and observations.

For the purposes of this study, we considered hindcasts initiated on 1 February and 1 November. The 1 February hindcasts are particularly relevant to eastern Africa, where the March–May long rains contribute a significant portion of annual total rainfall and represents the major growing season both for agricultural crops and natural vegetation (primary food source for elephants). The 1 November hindcasts are initiated at the start of southern Africa's single rainy season and are also relevant to eastern Africa's October–December short rains, which bring the first life-saving rains after a prolonged dry season (June–September).

Because drought that persists over more than a single season is a rare event, there is value in considering as long a time series as possible. However, to maintain consistency with the climate change analyses, in the main article, skill assessments for 1960–1990 are shown. The results from the full dataset are included as Supplementary information.

2.1.3 | Precipitation observations

Both the seasonal hindcasts and historical CMIP6 data are compared against the monthly Global Precipitation

Climatology Centre (GPCC) precipitation observations. GPCC was chosen primarily for its consistent climatology and long time span. Although there are considerable discrepancies between different observational datasets over Africa, the long-term climatologies agree reasonably well (Maidment et al., 2017).

In this study, the GPCC 1° resolution v7 full data reanalysis (GPCC_FD) was used (https://downloads.psl.noaa.gov/Datasets/gpcc/full_v7/). GPCC_FD is based on a large quality-controlled rain gauge dataset. In order to provide a robust climatology, only gauges with at least 10 years of data are included. Monthly rainfall estimates are provided at every land point on the globe by interpolating precipitation anomalies and superposing them on the GPCC climatology V2020 (Schneider et al, 2017). The GPCC_FC v7 is available for 1891–2019. For a full description of the dataset, see Becker et al. (2013), Reason (2017).

2.1.4 | Elephant locations

Spatial data for the current range of African savannah elephants (*L. africana*) were obtained from the International Union for the Conservation of Nature (IUCN) Red List of Threatened Species (IUCN SSC African Elephant Specialist Group, 2021). We considered current range to include all elephant locations listed as either 'Extant (resident)', 'Possibly extant (resident)' and 'Extant and reintroduced (resident)'. The current range of African elephants has been constrained by the expansion of human-dominated landscapes. For projections (Section 2.1.1), we assumed the range currently available to elephants would persist throughout the 21st century. However, there is the potential for elephant ranges to further shrink or expand under future climates and with habitat restoration efforts, and though interesting, was beyond the scope of this work.

2.2 | Methods

2.2.1 | Elephant-relevant drought metrics

In this study, in addition to 3-month cumulated precipitation, the 3-month SPI is used to represent drought. SPI is calculated using the standard method presented, for example, in Keyantash et al. (2023). In this study, SPI is calculated relative to a 1960–1990 climatology. We choose to analyse SPI over a more agriculturally relevant variable, such as standardised precipitation evapotranspiration index (SPEI), primarily because seasonal forecasts of 3-month SPI are operationally produced by the main forecasting centres in sub-Saharan Africa. SPI is essentially a standardised and normalised metric of precipitation. As such, it is an operationally useful metric of meteorological drought because it allows comparison between regions with differing rainfall climates.

Negative SPI values can be interpreted as follows:

- $SPI < -2$ severe drought
- $-2 < SPI < -1.5$ moderate drought
- $-1.5 < SPI < -0.75$ mild drought

As is described later in the article, elephants are particularly sensitive to unfavourable conditions that recur over two consecutive seasons or more. For this reason, we focus on drought conditions ($SPI < -0.75$) in the critical onset period of the rainy seasons, when elephants are at their least resilient (i.e., February in East Africa and November and southern Africa) that persist for two or more consecutive seasons.

2.2.2 | Skill assessments

This article does not aim to provide a comprehensive skill assessment of seasonal forecasts (see, e.g., Young et al., 2020 for a more detailed evaluation). Therefore, the formal skill assessment was restricted to two metrics: Pearson correlation coefficient and relative operating characteristic (ROC).

The Pearson correlation coefficient ('r') compares seasonal hindcasts against observed seasonal rainfall cumulations. Broadly speaking, 'r' represents the degree to which the hindcasts are linearly related to the observations. Perfectly correlated hindcasts/observations would have an 'r' of 1 and perfectly anti-correlated values would have an 'r' of −1. For 30 years of values, correlations with a magnitude less than ~0.3 may be considered statistically insignificant (Livezey & Chen, 1983).

The ROC measures the skill of probabilistic forecasts in detecting a user-defined event by comparing the probability of detecting an event (hit rate) against the probability of a false-alarm. In this context, an event is detected if a particular probability threshold is breached. For a low probability threshold, in less skilful forecasts, both the hit rate and false alarm rate would be high. For a high probability threshold, the converse would be true. This notion can be formalised by plotting hit rate against false alarm rate for a range of probability threshold values and calculating the area under the resulting curve (ROC-AUC). A perfect forecast would have a ROC-AUC of 1, and a forecast with climatological skill would have a ROC-AUC around 0.5. For this study, the ROC-AUC was

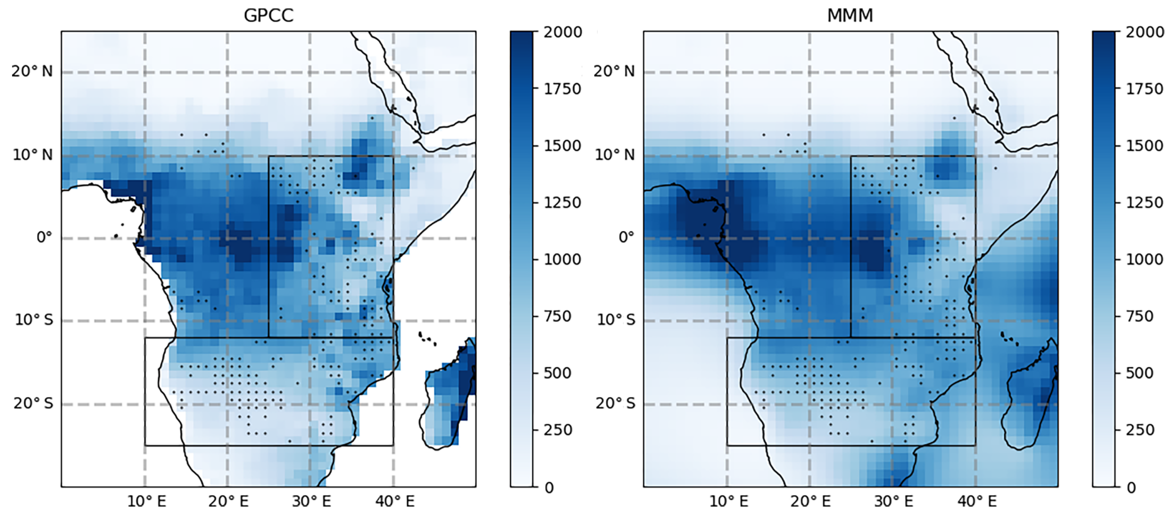

FIGURE 1 Mean annual precipitation (mm) over Africa in Global Precipitation Climatology Centre (GPCC) observations (left panel) and for the CMIP6 multi-model mean (MMM) (right panel) for 1960–1990. The rectangles denote the north and south study areas and the dots show present day elephant ranges.

derived for the detection of drought events (defined as SPI of <−0.75).

Although the ROC-AUC is a useful way of formally quantifying the skill of a forecast system, it is not an intuitive metric. It is therefore difficult for a user to decide, based on ROC-AUC alone, whether or not a forecasting system is producing actionable information (Coughlan de Perez et al., 2016). For this reason, maps of ROC-AUC have been supplemented by contingency tables for all 'elephant points' in the northern and southern study regions. The contingency tables were derived using a probability threshold of 0.5.

3 | RESULTS

3.1 | Model representation of precipitation in the study areas

African savannah elephants predominantly inhabit eastern and southern Africa, and these regions form the basis of this study (Figure 1). Elephants are ecological generalists and can survive in landscapes ranging from the deserts of Namibia to the sub-tropical forests of Mozambique (Chase et al., 2016). They are well-adapted to seasonal fluctuations in resource availability, though changes in the spatiotemporal availability of food and water drive elephant movement patterns, and elephants existing in climatologically drier landscapes typically range over larger distances in search of sufficient resources (Loarie et al., 2009).

Figure 2 shows the seasonal cycle in precipitation in both study areas. Both the mean for all points and the mean for elephant locations only are shown. The northern region (East Africa) has two rainy seasons, resulting from the north–south migration of the ITCZ (Nicholson, 2017). The long rains start in February and end in May, and the short rains start in September and end in December. The differences between the seasonal cycle at all points and at elephant points only reflect the considerable complexity of the rainfall seasonality in East Africa (see Gissila et al., 2004).

Precipitation in the southern region is highest during the austral summer (November–February) and lowest during winter (Reason, 2017). However, the region has high interannual variability, especially in precipitation, so there can be strong deviations from 'typical' conditions both within a season and between years (C. Cook et al., 2004). Climatic conditions vary greatly over Southern Africa, with humid equatorial conditions, seasonally arid tropical conditions and subtropical conditions all found across the region (Hulme et al., 2001).

The comparisons between models and observations shown in Figures 1 and 2 show that in the northern study area (East Africa), the multi-model mean generally captures the spatial structure of annual precipitation well, apart from at the coast, where there is significantly less precipitation modelled than observed. In the south, however, the multi-model mean spatial structure appears smeared in comparison to the observed variability, with excessive precipitation in the south and too little precipitation in coastal areas. Figure 2 shows that there is considerable variation between model representation of the seasonal cycle in East Africa, with some models having more precipitation in the short rains (October–December season) than in the long rains (March–May season). This

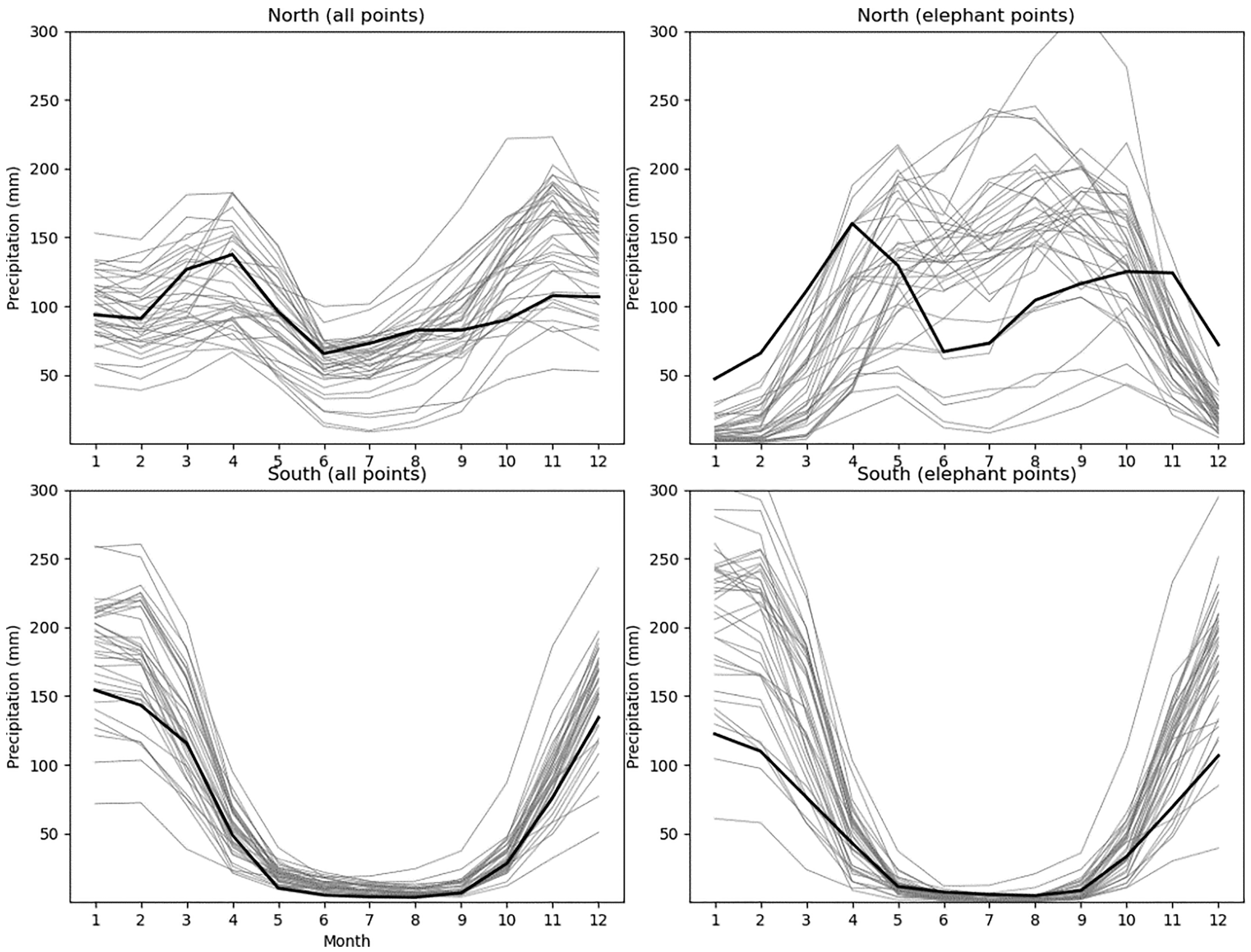

FIGURE 2 Mean seasonal cycle in precipitation for the north (top panels) and south (bottom panel) study areas as shown on Figure 1 for 1960–1990. The left panels are averaged over all points in the study areas and the right panels are for points within elephant ranges only. The thick line is Global Precipitation Climatology Centre observations and the thin grey lines are for the CMIP6 models.

is consistent with the published literature, which confirms that although there is improvement in CMIP6, compared to CMIP5 in the representation of the bi-modal seasonal cycle, significant variation between models persists, especially in their representation of the long rains (Ayugi et al., 2021). In southern Africa, Figure 2 shows that all of the models reproduced the overall shape of the seasonal cycle, but that there is large variation in the amount of precipitation during the main rainy season.

3.2 | Projected change in precipitation and SPI

The projected change under SSP 2–4.5 of annual mean SPI and annual total precipitation for the 2060–2090 period, compared to 1960–1990 is shown in Figure 3. The contrast between the projected change in precipitation and SPI north of ~10° S and precipitation further south is clear, with precipitation and hence SPI projected to increase in the north and decrease in the south. The right panels of the figure show the proportion of models that agree with the mean polarity of change. In most of the northern region, >80% of models agree on the polarity of change of both SPI and precipitation. In the south, the agreement is slightly lower for precipitation, although the model agreement for projected SPI is higher. As would be expected, around 10° S, where the multi-model projected signal of change shifts from wetter to drier, the model agreement is lower—reflecting the fact that while most models project the north–south divide in polarity of annual precipitation/SPI change, the latitude of the transition varies. Figure 4 displays the range of model projections for changes in SPI and precipitation, focusing on the grid squares where elephant communities are found in the present day. Consistent with Figure 3, the models agree that SPI is projected to decrease in the southern region and increase further north. It should be noted that

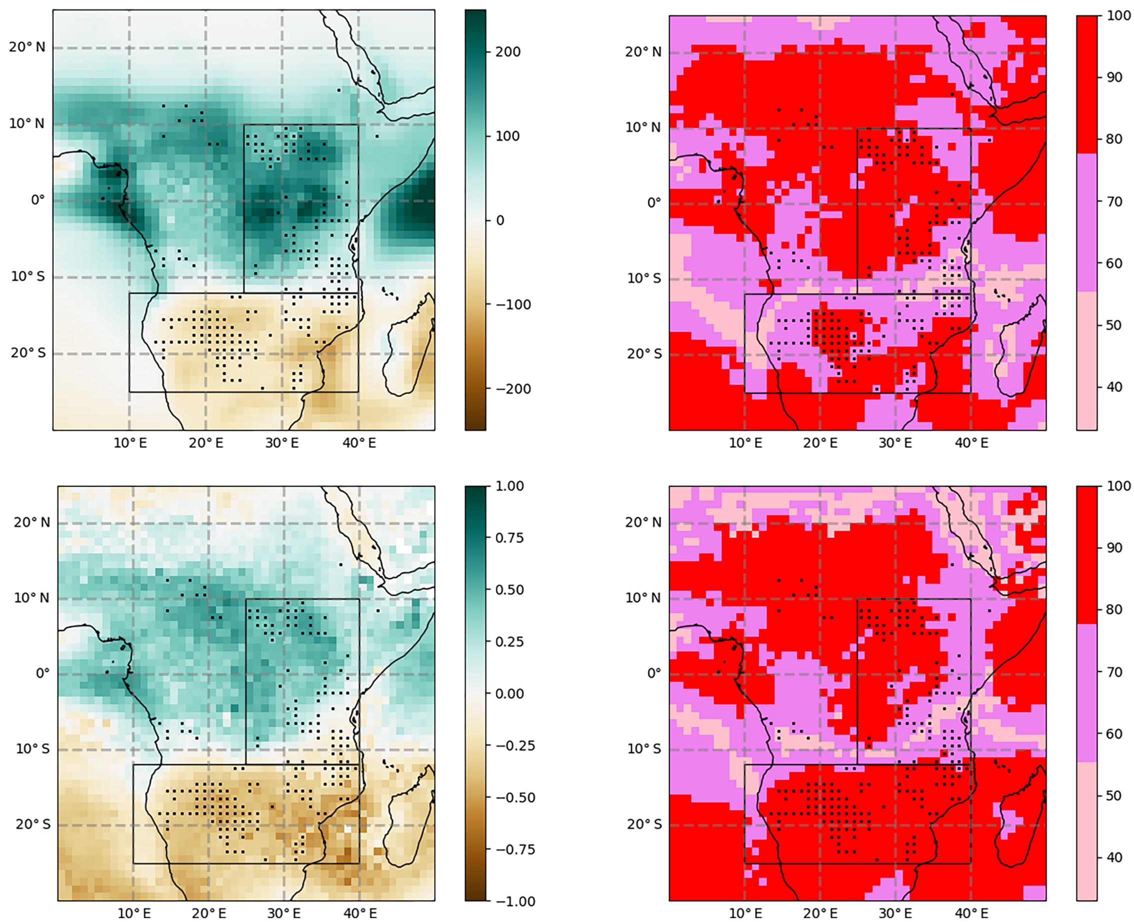

FIGURE 3 Projected change in annual precipitation (top panels) and SPI (bottom panels) comparing 1960–1990 against 2060–2090 under SSP 2–4.5 (SSP 2–8.5 shown in Figure S1). The left panels show the precipitation and SPI multi-model mean changes and the right panels show the percentage of models that agree on the polarity of the multi-model mean change (individual models and seasons shown in Figures S2–S25).

for both regions, although there is broad model agreement in the polarity of projected change, the magnitude of the projected changes varies.

The findings for southern Africa are consistent with previously published studies. In particular, the IPCC reports *high confidence* in the projected drying during the main rainy season, with increasing frequency of multi-year droughts (Dosio, 2017; Trisos et al., 2022; Zhao & Dai, 2017). More detailed studies of precipitation change in East Africa, however, suggest that the picture is more complicated than might be implied by the annual precipitation changes shown in Figures 3 and 4. Although the short rains (October–December) are consistently projected to lengthen and intensify (Dunning et al., 2018; Endris et al. 2019; Gudoshava et al., 2020), the projected changes in the long rains (February–May) are less certain due to lack of understanding of the driving mechanisms and inconsistencies between regional and global models (K. H. Cook et al., 2020; Lyon & Vigaud, 2017; Osima et al., 2018; Trisos et al., 2022).

Any change in drought occurrence has significant implications for elephants, with worsening of persistent drought being particularly dangerous. Elephants' large body size, hind-gut fermentation and relatively slow metabolism mean they are adapted to survive periods of poor vegetation quality and quantity (Owen-Smith, 1988). Their large body size and ability to store large fat reserves further creates a buffer to an underperforming rainy season (Pitts & Bullard, 1968; Sibly et al., 2013), but this buffer has its limits. Multiple consecutive failed rainy seasons deplete energetic reserves and leave elephants unable to replenish vital dietary nutrients (Pretorius et al., 2012). In these instances, milk-dependent calves die first as their mothers fail to meet the costs of lactation, then older individuals follow, whose worn teeth are unable to digest remaining woody vegetation (Boult et al., 2018). Poor body condition is further associated with increased parasite loads in elephants (Sánchez et al., 2018), and the struggle to access sufficient food may drive some individuals into farmland and human settlements, resulting in increased mortality from human–elephant conflict (Shaffer et al., 2019). It is therefore prolonged droughts, persisting across multiple rainy seasons, which are of particular significance for elephants.

Figure 5 shows that in the present-day climate, in most parts of the southern study area, drought that persists for more than one season is rare, but that multi-season droughts become more common in a future climate, reflecting the overall reduction in SPI. In the north, in contrast, although two-season droughts are more common in the present day, the frequency of such events is projected to reduce in the future.

3.3 | Seasonal forecast skill

The ability to forecast drought reliably on seasonal time scales opens the possibility of taking early mitigating action. The type of anticipatory action taken should be influenced by the skill of the forecasts, among other factors, such as the magnitude of the hazard, the feasibility

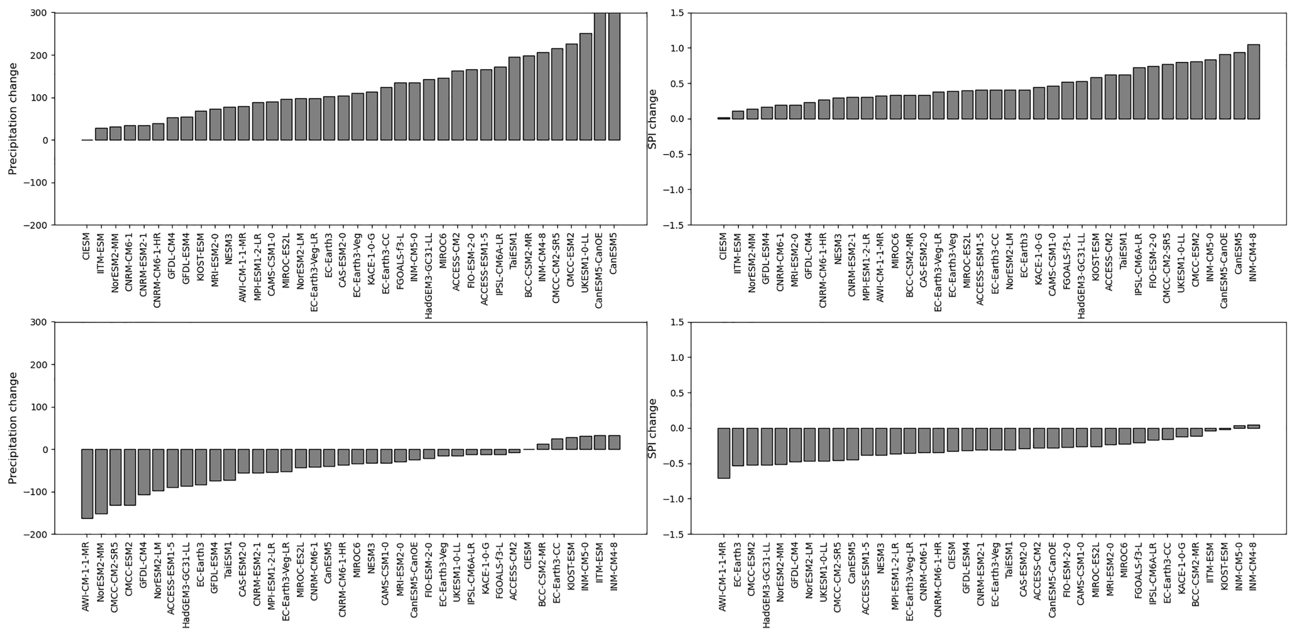

FIGURE 4 Projected change in annual standardised precipitation index (right) and precipitation (left) under shared socio-economic pathways (SSP) 2–4.5, comparing 2060–2090 against 1960–1990 for the north (top row) and south (bottom row) study regions—points within elephant ranges only. Additional plots for February–April and November–January seasons and for SSP 5–8.5 are shown in Figures S26–S37.

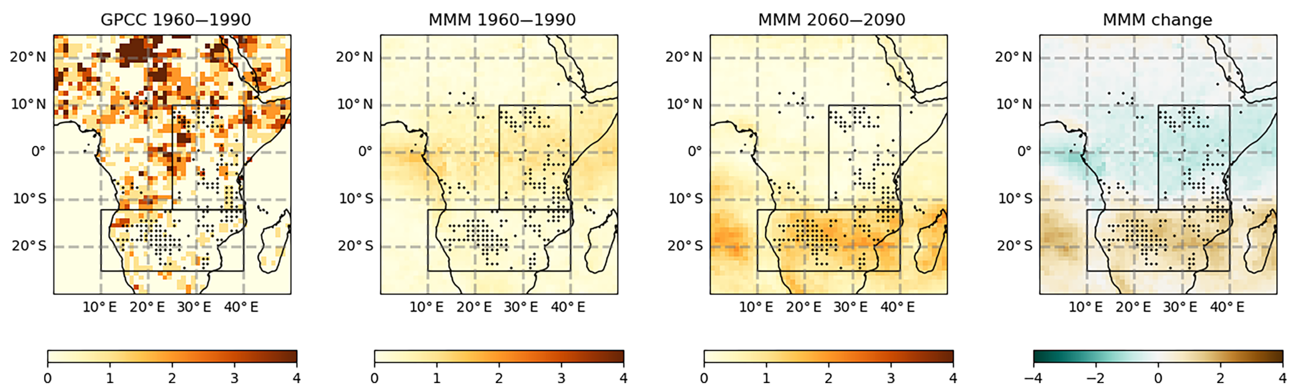

FIGURE 5 Multi-model mean number of incidences of two consecutive rainy seasons with moderate or severe drought (standardised precipitation index < −0.75) within a 30-year period. From left to right: Global Precipitation Climatology Centre 1960–1990, multi-model mean 1960–1990, multi-model mean 2060–2090 (shared socio-economic pathways [SSP] 2–4.5) and difference between the two periods. SSP 5-8.5 is shown in Figure S38.

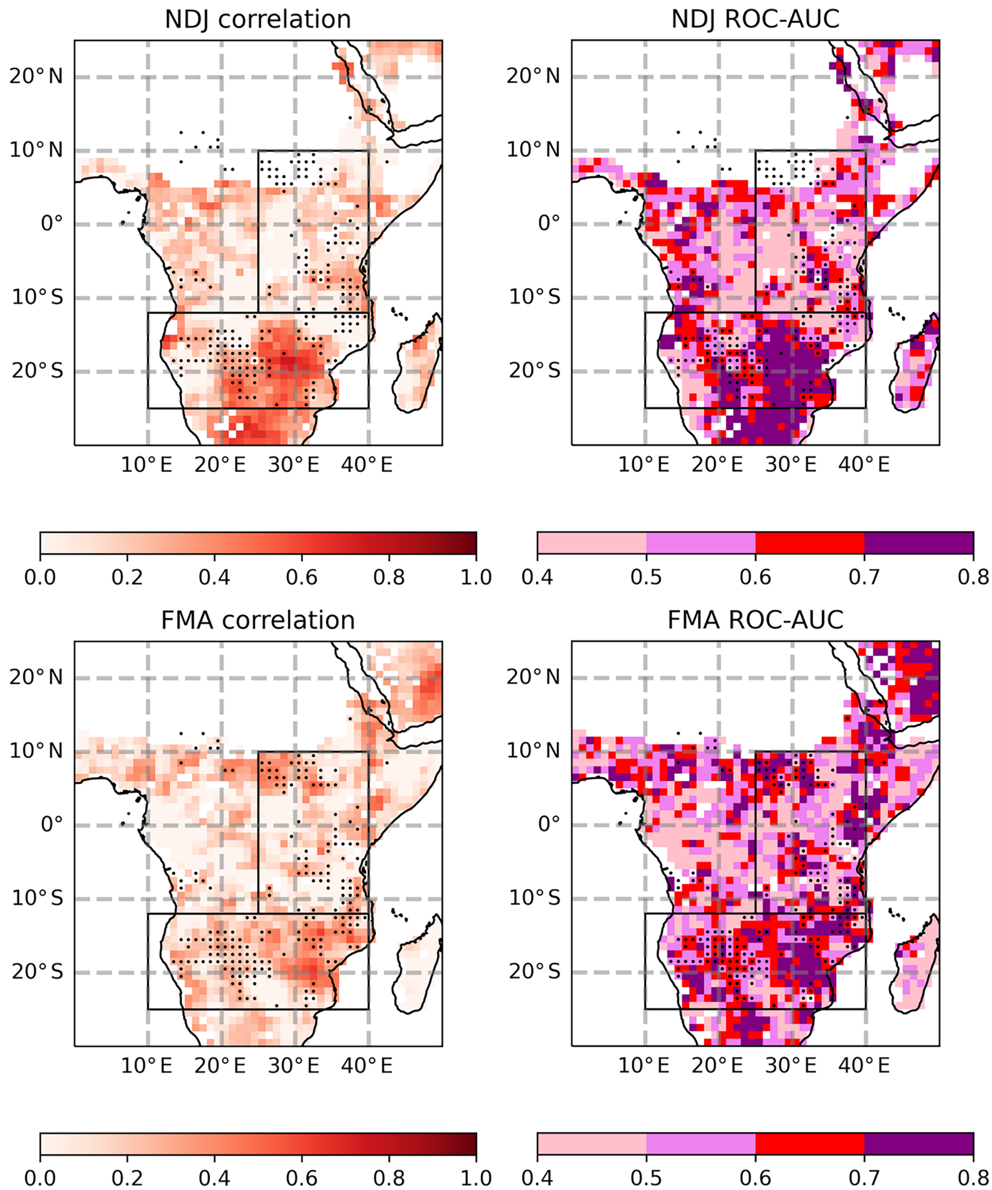

FIGURE 6 Comparison between observed (Global Precipitation Climatology Centre) and hindcast November–December (top panels) and February–April (bottom panels) standardised precipitation index (SPI) for hindcasts initiated on 1 November and 1 February, respectively. Left panels: Pearson correlation coefficient; Right panels: ROC- AUC for predicting a drought, defined as SPI < -0.75. Additional skill assessments shown in Figure S39.

of action and the vulnerability of the population. If forecasts lack sufficient skill, the focus should be on low regret actions (those which (a) are useful to do regardless of experienced drought, or (b) require little cost, resource and time to implement such that if a forecasted drought does not materialise, early action is not regrettable), while if decision-relevant forecasts are skilful, a wider range of actions may be available to the sector (including those which require a larger initial investment of resources). Figure 6 shows two metrics of skill: the Pearson correlation coefficient between observations and hindcasts and the ROC-AUC score for detection of drought (defined as SPI < -0.75). The metrics are calculated for both the February–April and November–January seasons, which approximately represent the critical first half of the main rainy seasons in the northern and southern regions, respectively. It is evident that for both regions and seasons, there is some skill compared to climatology for April and January SPI forecasts initiated in February and November. It might be expected that the skill of forecasts for the November-initiated forecasts would be significantly higher because of the increased predictability resulting from the influence of El Nino and the Indian Ocean Dipole (IOD; Walker et al., 2019). However, these assessments suggest that, although the skill is slightly better for the November initiated forecasts compared to those initiated in February, the difference is small.

The question arises as to whether there is sufficient skill in the seasonal forecasts to be useful to the conservation sector. As was described earlier, a key issue for elephants is a poor start to the rainy season following a drought (can lead to elevated elephant mortality and an escalation in human–elephant conflict). The impact-relevant metric of drought chosen for further analysis was, therefore, 3-month SPI with an event deemed to have occurred if the SPI is below −0.75 in the year following a drought. To capture the critical first phase of the wet seasons in eastern and southern Africa, the analysis was conducted for hindcasts initiated on 1 February and 1 November. An example contingency table for these events is shown in Table 1. The results suggest that, in spite of the generally reasonable skill in southern Africa for prediction of November–January SPI (Figure 6), at locations where elephants are found, the false alarm rate is high. It should be noted, however, that the example contingency table is for the season and region with the greatest skill (NDJ Southern Africa). Results for the other seasons and regions are given in Supplementary materials (Figure S38 and Tables S2–S5), which also includes contingency tables for prediction of SPI < −0.75 in all years (i.e., not just following a drought). Arguably, our findings suggest that even in the region/season with greatest skill only low regret decisions can be based on these forecasts, limiting their practical utility.

TABLE 1 Example contingency table for forecasting of subsequent droughts (standardised precipitation index < −0.75) in the season following a drought (NDJ for southern Africa).

	Forecast event	Forecast no event
Observed event	32 (hits)	38 (misses)
Observed no event	60 (false alarms)	247 (correct negatives)

Note: An event is said to have occurred if the forecast probability is >0.5 (Additional contingency tables given in Tables S2–S5). False alarm rate = 0.13. Probability of detection = 0.35.

4 | DISCUSSION

Across Africa's savannah landscapes, drought is widely perceived as a natural phenomenon and one which is important for the natural regulation of wildlife populations. However, with the expansion of human-dominated landscapes across sub-Saharan Africa, elephants' natural adaptation strategies (namely migration) are being eroded, meaning drought may have disproportionate impacts on elephant populations under combined climate and land-use change scenarios (Boult et al., 2019). This ultimately has implications for the multidimensional benefits derived from elephant populations, including tourism revenues and ecosystem function. Further, in mixed-use ecosystems, drought can exacerbate human–elephant conflict, now the leading cause of anthropogenic elephant mortality in some locations and a significant threat to human well-being (Mayberry et al., 2017).

Our study considered projected changes in drought from the point of view of elephant conservation in eastern and southern Africa. Because elephants are particularly vulnerable to successive drought seasons, we focused on drought conditions that recur over two or more seasons. Analysis of present-day observations and historical model integrations (Figure 5) showed that in the present day in East Africa, persistent drought occurs occasionally while in the southern study area, it is nearly unknown. The potential impact of future increased occurrence of persistent drought is severe for the elephant populations of Africa. Consistent with previous work, we found that precipitation is projected to increase in central and northern Africa over the 21st century and to decrease in the south (Trisos et al., 2022). The polarity of change was broadly consistent between models, albeit with variation in magnitude and some uncertainty in the projections for the long rains in East Africa. The agreement between models increases our confidence in the projections, especially for the southern Africa drying.

Given that the risk of persistent drought in southern Africa is projected to worsen, the question arises as to how the increasing risk to elephants might be managed over the next decades. In the humanitarian sector, anticipatory action has been shown to substantially reduce climate-related risks, but only if the challenges of working with uncertain data and multiple hazards can be incorporated into early action plans (Boult et al., 2022; de la Poterie et al., 2023). In this context, the conservation sector may be able to learn lessons from the humanitarian and agricultural sectors, where the potential value of seasonal forecasts in a changing climate has long been recognised (Winsemius et al., 2014). In East Africa, preliminary conversations are underway around the use of DEWS in ecosystem management and conservation planning. This contrasts with existing approaches that make little use of forecast information and instead adopt a responsive approach to drought management. There is the potential to make use of seasonal rainfall/SPI forecasts routinely produced by regional climate service providers to act in anticipation of drought, improving preparedness and ultimately reducing drought impacts. This may see conservation and wildlife management organisations strategically positioning resources to manage human–elephant interactions, advising pastoralists on the management of grazing resources and destocking rates ahead of key seasons and timing ecosystem restoration efforts (e.g., reseeding) to maximise success. As the risk of prolonged drought shifts from East Africa in the present day to southern Africa in the future, there is great opportunity to develop strategies for the management of drought risk to elephants in East Africa which can later be transferred, via South–South learning, to practitioners in the south of the continent. Each action has a cost, probable effectiveness and requires a given amount of time to implement. Some of the suggested actions (e.g., supplementary feeding) are already implemented in response to drought impacts (i.e., an increase in rates of crop-foraging by elephants), so the use of forecast information only acts to implement these actions earlier to prevent impacts and does not necessarily incur additional costs. In the example given here, where the false-alarm rate is high, low-cost and low-regret actions are preferable as the chance of acting in vain is high. Implementing organisations should consider their own financial and operational constraints to balance the costs, effectiveness, lead times and risks of inaction to develop early action protocols defining forecast danger and probability levels to trigger each potential action, and given current forecast skill, must accept that some actions are associated with unacceptable levels of uncertainty and may only be implemented responsively.

Although our assessments agree with previously published work that seasonal forecasts of precipitation in southern and East Africa have better skill than climatology (de Andrade et al., 2021; Young et al., 2020), the high rate of false alarms and the large number of misses in elephant-inhabited regions may limit the utility of the forecasts for the conservation sector. Nevertheless, there is substantial predictability in the African climate system, related to variability in Indian Ocean and Pacific SST (Black, 2005; Black et al., 2003) and advances continue to be made in understanding the large-scale drivers of subseasonal to seasonal variability relevant for African predictability (Moron & Robertson, 2020; White, 2022). Understanding how drivers such as the Madden Julian Oscillation (MJO; Zaitchik, 2017), El Niño Southern Oscillation (ENSO; MacLeod et al., 2021), regional SST anomalies (Hirons & Turner, 2018) and land-surface conditions (Talib et al., 2023) interact and change the local environment to cause high-impact weather across Africa (e.g., through modulating wind shear, moisture availability or vertical instability) is key to interpreting and appropriately calibrating our models. A better understanding of this regime-dependent skill—where, when and why our extended-range forecasts exhibit higher skill—if communicated, monitored and evaluated effectively, has huge potential to support better decision-making in conservation applications across Africa in the future.

Improved understanding of regime dependent skill is relevant to another intriguing question: whether the predictability of the African climate, and hence the skill of seasonal forecast models, will be modulated by climate change. There is good evidence that the skill of ENSO forecasts has varied during the 20th century (Weisheimer et al., 2020). There is, moreover, evidence that precipitation may become inherently more predictable as a result of climate change (Phong et al., 2023). Understanding how climate regimes may affect the predictability of African precipitation, and how the occurrence of such regimes will be affected by climate change will provide further insights into this question.

Another potential avenue for progress is in identifying metrics and variables that are both more impact-relevant and more skilfully predicted than seasonal total precipitation. At the simplest level, 1-month cumulations of precipitation are more skilfully forecast than 3-month cumulations (see Supplementary information). Thinking beyond precipitation, the TAMSAT-ALERT system combines historical observations and meteorological forecasts into predictions of seasonal soil moisture. In East Africa, in the short rains, seasonal TAMSAT-ALERT soil moisture forecasts are substantially more skilful than seasonal precipitation forecasts (ROC-AUC ∼0.8 compared to ROC-AUC ∼0.6) and are able to capture antecedent soil moisture conditions associated with previous drought (Boult et al., 2020).

While the provision of reliable forecast information for conservation has huge potential to support early action and planning decisions, meteorological forecast verification alone is necessary but not sufficient for weather and climate services to be effective (Hirons et al., 2021; Lemos et al., 2012; Vaughan & Dessai, 2014). There is increasing recognition that actionable and reliable services require an iterative dialogue between the disciplines and stakeholders involved to combine knowledge and jointly develop services which address issues of shared concern (Visman et al., 2018), through a process known as co-production (Bremer et al., 2019; Carter et al., 2019; Vincent et al., 2020). Such an approach shifts the user, in this context the conservation practitioner, from a recipient of forecast information to a participant in the knowledge and service generation process (Vincent et al., 2020), for instance, drawing on conservation practitioners' understanding of species' ecology to define relevant forecast thresholds and early actions, thereby increasing the likelihood that bespoke forecast information is 'useful, usable and used' (Boaz & Hayden, 2002; Hirons et al., 2021). For example, this could involve user-directed iterations to the visualisation, communication or content of forecasts (Gudoshava et al., 2022; Hirons et al., 2023; Lawal et al., 2021) or applying user-defined thresholds for specific decision-making applications (Dione et al., 2022). However, it is also increasingly clear that the iterative co-production process itself is extremely resource intensive (Hirons et al., 2021) and to be effective, stakeholder engagement, monitoring and evaluation need to be institutionalised as the operational norm (Visman et al., 2022).

5 | CONCLUSIONS AND RECOMMENDATIONS

In conclusion, the climate change issue may be perceived by some as distinct from the seasonal prediction problem. Much emphasis in the scientific community is placed on reducing uncertainty in climate change projections and hence improving our ability to quantify potential impacts. However, as the reality of a changing climate becomes apparent, the need for all sectors to adapt becomes urgent. In this context, there is a growing recognition of the role of early warnings and subsequent anticipatory action—as exemplified by the WMO's *Early Warnings for All* initiative.

Our study has viewed climate change and seasonal prediction through the lens of the conservation sector in sub-Saharan Africa. Our results highlight some of the specific dangers that climate change poses to elephant communities in regions likely to experience a worsening of drought. Bespoke seasonal forecast skill assessments, targeting metrics that are both sector relevant and affected by climate change, illustrate the limitations and the potential value of our current systems. It is clear that preparedness and capacity for anticipatory action could be a key element of building the climate resilience for the conservation sector—but only if the practical utility of forecasts is substantially improved. Over the next decades, progress will depend on the commitment of meteorologists and practitioners to the co-production of actionable meteorological predictions and projections.

Based on our findings, and on our review of the literature in this area, we thus recommend the following:

- Improved calibration of seasonal forecasts for African precipitation, building on our understanding of the impact of climate regime on skill.
- Strengthening of links between the meteorological and conservation sectors to facilitate co-production of relevant seasonal forecasts.
- Further research on drought impacts on elephants, with the aim of identifying a range of locally relevant, low-regret actions that can be taken in advance of the rainy season to mitigate the impact of severe drought.

Finally, based on our climate change assessments, we recommend a strengthened focus in all of these areas on southern Africa, where drought is projected to get significantly worse in the 21st century.

AUTHOR CONTRIBUTIONS

Emily Black: Conceptualization (equal); formal analysis (equal); writing – review and editing (equal). **Victoria Boult:** Conceptualization (equal); data curation (equal); writing – review and editing (equal). **Linda Hirons:** Conceptualization (equal); writing – review and editing (equal). **Steven Woolnough:** Conceptualization (equal); writing – review and editing (equal).

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DATA AVAILABILITY STATEMENT

All data used within this article is in the public domain. Code for production of the figures is available on reasonable request to Emily Black (e.c.l.black@reading.ac.uk).

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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