

RESEARCH ARTICLE OPEN ACCESS

Near-Term Forecasting of Terrestrial Mobile Species Distributions for Adaptive Management Under Extreme Weather Events

Rachel Dobson^{1,2}  | Stephen G. Willis² | Stewart Jennings³ | Robert A. Cheke⁴ | Andrew J. Challinor³ | Martin Dallimer⁵

¹Sustainability Research Institute, School of Earth and Environment, University of Leeds, Leeds, UK | ²Conservation Ecology Group, Department of Biosciences, Durham University, Durham, UK | ³Institute for Climate and Atmospheric Science, School of Earth and Environment, University of Leeds, Leeds, UK | ⁴Natural Resources Institute, University of Greenwich, Chatham, Kent, UK | ⁵Centre for Environmental Policy, Imperial College London, London, UK

Correspondence: Rachel Dobson (erdo@leeds.ac.uk; rachel.a.dobson@durham.ac.uk)

Received: 26 February 2024 | **Revised:** 2 October 2024 | **Accepted:** 22 October 2024

Funding: This research was supported by the Leeds-York-Hull Natural Environment Research Council (NERC) Doctoral Training Partnership (DTP) Panorama (NE/S007458/1) and the Biotechnology and Biological Sciences Research Council through UK Research and Innovation as part of the Global Challenges Research Fund, AFRICAP program (BB/P027784/1).

Keywords: climate adaptation strategies | climate change | dynamic species management | extreme weather events | near-term forecasting | *Quelea quelea* | red-billed quelea | seasonal forecasting | species distribution modelling

ABSTRACT

Across the globe, mobile species are key components of ecosystems. Migratory birds and nomadic antelope can have considerable conservation, economic or societal value, while irruptive insects can be major pests and threaten food security. Extreme weather events, which are increasing in frequency and intensity under ongoing climate change, are driving rapid and unforeseen shifts in mobile species distributions. This challenges their management, potentially leading to population declines, or exacerbating the adverse impacts of pests. Near-term, within-year forecasting may have the potential to anticipate mobile species distribution changes during extreme weather events, thus informing adaptive management strategies. Here, for the first time, we assess the robustness of near-term forecasting of the distribution of a terrestrial species under extreme weather. For this, we generated near-term (2 weeks to 7 months ahead) distribution forecasts for a crop pest that is a threat to food security in southern Africa, the red-billed *quelea* *Quelea quelea*. To assess performance, we generated hindcasts of the species distribution across 13 years (2004–2016) that encompassed two major droughts. We show that, using dynamic species distribution models (D-SDMs), environmental suitability for *quelea* can be accurately forecast with seasonal lead times (up to 7 months ahead), at high resolution, and across a large spatial scale, including in extreme drought conditions. D-SDM predictive accuracy and near-term hindcast reliability were primarily driven by the availability of training data rather than overarching weather conditions. We discuss how a forecasting system could be used to inform adaptive management of mobile species and mitigate impacts of extreme weather, including by anticipating sites and times for transient management and proactively mobilising resources for prepared responses. Our results suggest that such techniques could be widely applied to inform more resilient, adaptive management of mobile species worldwide.

Stephen G. Willis, Stewart Jennings, Robert A. Cheke, Andrew J. Challinor contributed equally to this study.

This is an open access article under the terms of the [Creative Commons Attribution](https://creativecommons.org/licenses/by/4.0/) License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited.

© 2024 The Author(s). *Global Change Biology* published by John Wiley & Sons Ltd.

1 | Introduction

With every passing year, record-breaking weather is increasingly commonplace (O'Kane 2024; Poynting 2024) as extreme events increase in frequency, intensity and extent worldwide. This phenomenon is a result of ongoing anthropogenic-induced climate change; rising global temperatures from the emission of greenhouse gases are altering atmospheric and oceanic conditions and increasing weather variability (Seneviratne et al. 2021). Encompassing intense heatwaves and droughts, through to severe flooding and storms, extreme weather events have severe and detrimental consequences for ecological and human systems (Ummenhofer and Meehl 2017). These events put species at risk of extinction, disrupt the provision of ecosystem services, and present challenges to both food security and human health (Murali et al. 2023; Slingo et al. 2005; Haines et al. 2006). Such impacts arise through several mechanisms (Maxwell et al. 2019), including habitat destruction by floods or storms (Wiley and Wunderle 1993), water deficits from severe droughts (Prugh et al. 2018), physiological stress from temperature extremes (McKechnie, Hockey, and Wolf 2012), and disturbances increasing ecosystem vulnerability to biological invasion (Diez et al. 2012). Thus, the timely development of effective climate adaptation strategies is critical (New et al. 2022). These strategies involve prepared responses that mitigate negative impacts and reduce the vulnerability of species, systems and society to climate changes.

Mobile species, which include nomadic or migratory organisms that engage in substantial movements within their life cycle, are integral components of ecosystems worldwide (Teitelbaum and Mueller 2019; Runge et al. 2014). Consequently, many mobile species are important for supporting global biodiversity, hold great cultural significance, and contribute economic value through ecotourism. For instance, the nomadic Mongolian gazelle *Procapra gutturosa* is a key grazer regulating Mongolia's steppe (Nandintsetseg et al. 2019), while the scarlet-chested parrot *Neophema splendida* is revered for its distinctive beauty in Australia (Runge and Tulloch 2018). In a broader context, across many nations and species, migratory cuckoos and swallows hold great cultural value as harbingers of new seasons (López-Hoffman et al. 2017), while salmon can offer key ecosystem services, including economic benefits and biodiversity support (Walsh et al. 2020). However, some mobile species like the red-billed quelea *Quelea quelea* and the desert locust *Schistocerca gregaria* are considered pests, causing considerable agricultural damage and economic losses in Africa (Elliott 1990; Zhang et al. 2019). Extreme weather events drive high variability in mobile species distributions because individuals move flexibly in response to atypical conditions, such as by novel occupation of refugia (Dean, Barnard, and Anderson 2009) or shifting migration timing (Visser 2008; Tøttrup et al. 2012). Through driving these rapid and unforeseen changes in mobile species distributions, extreme weather events may lead to adverse consequences for society and the environment. For instance, mobile species populations may decline if individuals are compelled to leave protected areas or enter areas with new threats (Runge et al. 2014). Conversely, the negative impacts of pest or invasive mobile species may be exacerbated by novel or unexpected outbreaks as individuals change their distributions (Sutherst et al. 2011). To mitigate these negative impacts of changing

climates, we need to develop adaptive management strategies for mobile species under extreme weather.

Adaptive management strategies for mobile species and their associated impacts could involve dynamic management actions (Reynolds et al. 2017; Runge and Tulloch 2018). These are transient actions to manage mobile species on a temporary basis, such as short-term rental of habitat for protected area placement (Runge et al. 2014) or targeting local and well-timed control measures for pest species (Zhang et al. 2019). Managers can adjust the timing, extent, and location of management to track species' movements and flexibly respond to short-term environmental changes. In addition to the increased efficacy of these adaptive approaches (Dunn et al. 2016), transient actions could increase landowner cooperation, cost efficiency, and resilience of the management strategy under long-term climate change by better mitigating extreme weather impacts (Reynolds et al. 2017; Bull et al. 2013). However, such approaches depend on having information on where individuals will be at any point in time.

Near-term (or seasonal) ecological forecasting is an emerging field that aims to inform adaptive management by utilising meteorological forecasts for early warning of environmental conditions up to 1 year ahead, at hourly to monthly intervals (Tulloch et al. 2020). Similarly to how advanced near-term weather forecasts help humans adapt their behaviour, near-term ecological forecasting holds potential utility in anticipating and managing ecological changes (Dietze et al. 2018). Near-term forecasting of mobile species' intra-annual distributions could anticipate changes under extreme weather and inform proactive, adaptive management. However, at present, the few examples of near-term distribution forecasts are limited to a small number of marine mammals and commercial fish species to inform dynamic management, such as establishing spatial zoning restrictions or identifying optimal sites/timings for moving vessels (Barlow and Torres 2021; Brodie et al. 2017; Hobday et al. 2016). By contrast, the near-term forecasting of terrestrial species distributions for dynamic management has been largely ignored. Near-term forecasts of population dynamics have been developed to alert to outbreaks of disease, pests and prey species (Clark et al. 2022; White et al. 2019; Kleiven et al. 2018), but these lack the spatially explicit distributional estimates essential for targeting management. Given the pivotal roles of mobile species in many terrestrial systems (Runge et al. 2014), this knowledge gap needs to be addressed to understand whether their distributions can be forecast accurately, and at appropriate timescales and resolutions, for adaptive management purposes.

Near-term forecasts of mobile species distributions can be generated by employing dynamic species distribution modelling (D-SDM). D-SDMs have developed from static SDMs, which have been developed over recent decades (Guisan and Thuiller 2005; Zimmermann et al. 2010). D-SDMs utilise historical relationships between species occurrence and short-term environmental conditions to project dynamic distribution suitability under past or future environmental conditions (Elith, Kearney, and Phillips 2010; Milanese, Della Rocca, and Robinson 2020). When developing near-term ecological forecasts, uncertainty can arise from multiple sources, including from underlying model variables and structure, and from stochastic and extreme conditions (Doblas-Reyes et al. 2013). This uncertainty must be quantified

and considered when assessing possible outcomes and risks of dynamic management decisions (Dietze et al. 2018). The uncertainty of near-term forecasts of mobile species distributions may be increased during extreme weather events (Muhling et al. 2020). This is because extreme conditions often surpass those previously recorded in past and current species ranges, and, therefore, D-SDM projections based solely on historical relationships may be inaccurate. While studies in marine environments indicate robust near-term forecast performance during extreme weather events (Barlow and Torres 2021; Brodie et al. 2023), this has not yet been explicitly investigated in terrestrial spaces.

To address these gaps in our knowledge, we assess whether the near-term distribution of a highly mobile terrestrial species can be accurately forecast, including under extreme weather events. We then explore the value and operability of these forecasts for informing adaptive species management to mitigate the impacts of altered species distributions under extreme weather. For this, we generate near-term distribution forecasts for the red-billed quelea (hereafter referred to as quelea) up to 7 months ahead, which threatens food security across its range in sub-Saharan Africa, and assess forecast accuracy through hindcasting. We chose this species because it is a crop pest, is highly mobile, and its opportunistic life history facilitates rapid and unforeseen outbreaks during extreme drought events in southern Africa (Elliott 1990). During such events, abiotic stresses can greatly diminish crop yields (Knox et al. 2012), and so minimising additional pest-driven yield losses is critical to food security. The timely development of an adaptive pest management tool is especially important as extreme droughts are projected to intensify across this pest's range in the future (Niang et al. 2014). Ultimately, we envisage our study will encourage these approaches to be applied to other mobile species worldwide and inform adaptive management to mitigate negative impacts from our changing global climate.

2 | Materials and Methods

2.1 | Case Study Species and Region

Quelea are considered the world's most abundant wild bird, with an estimated population of 1.5 billion (Craig 2020). They are granivorous, nomadic birds of sub-Saharan Africa that are serious pests because they consume staple cereal crop seed, including wheat, sorghum and rice (Elliott 1990), locally causing up to 94% yield loss (Rodenburg et al. 2014). Consequently, their populations are frequently controlled to reduce impacts on food security. The dominant control method is lethal destruction by spraying aggregations with the pesticide fenthion, which is also toxic to non-target organisms (McWilliam and Cheke 2004). Alternative approaches utilising agronomic techniques to reduce crop damage (e.g., altering planting schedules or crop varieties to create a phenological mismatch between crop seed abundance and quelea presence) have been advocated (Cheke and El Hady Sidatt 2019). However, it can be challenging for farmers to know which, if any, of such agronomic changes may be suitable as, such approaches require forewarning of quelea distributions, which, thus far, have been difficult to predict.

Moreover, forewarning could improve the efficiency of pesticide spraying operations and reduce usage by targeting aggregations before young fledge or major crop damage occurs (Cheke and El Hady Sidatt 2019). Quelea are nomadic, dynamically tracking environmental suitability in space and time, and opportunistically redistributing to avoid poor conditions during extreme droughts (Elliott 1990). Near-term distribution forecasts could aid management efficiency by anticipating unexpected outbreaks, identifying sites for interventions before crop damage occurs, and informing farmers of agronomic decision risk.

Here, we forecast the distribution of the subspecies *Q. q. lath-amii* in southern Africa (Figure S1), focusing on this subspecies because its ecology and changing occurrence patterns are well-characterised (Jones 1989a). Quelea in southern Africa have two distinct life-stages breeding (December–May) and non-breeding (June–November). They are opportunistic colonial breeders whose colonies can be millions strong. Non-breeding roosts can be similarly numerous. Quelea movements are driven by both wild grass and cereal crop seed abundance, which in turn are governed by the regular movements of seasonal rain fronts. However, at a local scale, quelea distribution can be highly spatially and temporally heterogeneous (Ward 1971). Furthermore, developing a successful climate adaptation strategy is essential for this sub-species as it inhabits southern Africa, where over a fifth of the human population is currently malnourished (FAO et al. 2020). Moreover, under future climate change, this region is predicted to experience increases in severe droughts and associated crop yield declines (Niang et al. 2014; Knox et al. 2012). Therefore, minimising pest-driven yield loss here, through the development of adaptive management tools, will be highly impactful and mitigate negative socio-economic impacts of climate change. To assess the accuracy of near-term species distribution forecasting for informing quelea management, we employed hindcasting across the study period (2004–2016), a widely used method that replicates real-time forecasting systems in historical periods to evaluate outputs against observed data (Kell, Kimoto, and Kitakado 2016; Barnes et al. 2022; Woelmer et al. 2022).

2.2 | Extreme Weather Events

To identify extreme weather events during the study period (2004–2016), the one-month Standardized Precipitation-Evapotranspiration Index (SPEI) in each 0.5° cell across southern Africa (Beguería et al. 2023) was categorised (following McKee et al. 1993) as either: non-drought (> 0), mild (0 to -0.99), moderate (-1.00 to -1.49), severe (-1.50 to -1.99) or extreme (≤ -2). The SPEI quantifies drought on a standardised scale by assessing precipitation and evapotranspiration data over various time scales, which can indicate moisture deficiency or surplus relative to historical conditions (Beguería et al. 2014). The 1-month SPEI is derived by first computing the monthly difference between precipitation (P) and potential evapotranspiration (PET):

$$D = P - PET$$

This series is then fitted to a log-logistic distribution to estimate its parameters. The SPEI values are obtained by transforming the fitted distribution to a standard normal distribution:

$$\text{SPEI} = \Phi^{-1}(F(D))$$

where Φ^{-1} is the inverse of the standard normal cumulative distribution function and F is the cumulative distribution function of the log-logistic distribution. Monthly percentage cover of each class was calculated across the range of quelea in southern Africa (BirdLife International 2021).

2.3 | Species Distribution Modelling

To project quelea distribution under historical and near-term hindcast environmental conditions, we developed dynamic species distribution models (D-SDMs), which relate species spatiotemporal occurrence to short-term environmental conditions (Elith, Kearney, and Phillips 2010). To model these complex and non-linear relationships effectively, we used the machine-learning ensemble technique Boosted Regression Tree modelling (BRT, Elith, Leathwick, and Hastie 2008). Below we describe the response and explanatory variables used in BRT model fitting.

2.3.1 | Response Variable

Quelea occurrence records were collated from various sources, including the Global Biodiversity Information Facility, which comprises academic and citizen sciences datasets (GBIF 2021), and from pest control and government organisations (Table S1). Only records with coordinates demonstrating spatial uncertainty of < 100m were included for model fitting. Due to distinct niche requirements at each life stage, quelea records were separated into breeding or non-breeding localities for modelling. If records did not specify breeding or non-breeding behaviour, missing life-stage data were imputed through multiple imputations (Nakagawa and Freckleton 2008) informed by record location and month, which are known drivers of quelea breeding phenology (Jones 1989b).

As true absences were rarely recorded, we instead generated pseudo-absence points within close spatiotemporal buffers for fine-scale presence-absence comparisons. For each occurrence record, one pseudo-absence coordinate was randomly generated within a spatial buffer (250–500 km). Pseudo-absence record dates, required for extracting temporally matched explanatory variables, were randomly generated within a close temporal buffer (6–12 weeks either side) of the corresponding occurrence record date. These buffers were chosen to balance between being too close (in both spatial and temporal terms) for models to detect a difference, and too distant so that only coarse spatiotemporal drivers are identified (Vanderwal, Shoo, Graham, and Williams 2009). Spatial buffer extent was informed by quelea movement capabilities, and the temporal extent was informed by typical rates of change in their habitat (Ward 1971). Pseudo-absences were regenerated if they were within 6 weeks and the same 0.05° cell of a concurrent record. Quelea have a breeding cycle of about 6 weeks (Jaeger, Bruggers, and Erickson 1989), and so, conditions at a site are likely to remain suitable for this

period. Therefore, generating a pseudo-absence within 6 weeks of an observed presence at the same location could inaccurately suggest an absence.

2.3.2 | Explanatory Variables

Known drivers of quelea distribution were transformed into D-SDM explanatory variables (Table 1) that were temporally matched to occurrence and pseudo-absence records. Dynamic weather variables were calculated from CHELSA-W5E5 daily mean temperature and total precipitation data (Karger et al. 2022) that were spatially aggregated to 0.05° from 0.01°. The spatial resolution was coarsened to balance having sufficient detail for species distribution modelling with minimising overfitting and unrealistic precision associated with finer data. Resource variables were derived from MODIS Annual Land Cover datasets (Friedl and Sulla-Menashe 2019). For each resource variable listed in Table 1, each 0.004° MODIS Annual Land Cover cell was classified into “1” (presence) or “0” (absence) based upon the presence of land cover types associated with that resource, such as water bodies or preferred habitat. These binary data were then aggregated by sum to a spatial resolution of 0.05°, representing the relative abundance of a resource within each larger grid cell. Considering quelea can forage up to 10 km from a breeding colony or non-breeding roosting site to access resources (Elliott 1990), resource abundance was then summed across the equivalent spatial area surrounding each cell using the ‘dynamicSDM’ R package (Dobson et al. 2023). One exception was for the seed abundance resource variable; here, the binary classification depended not only on the presence of grassland and cereal cropland cells but also on being within the correct graminoid phenology stage on a date, such that seeds are available for quelea consumption (Appendix A1). The vegetation phenology stages were derived from the MODIS Annual Land Cover Dynamics dataset (Friedl, Gray, and Sulla-Menashe 2019), which classified vegetation as being in various stages, including “green-up”, “maturity” and “senescence,” based on trends in the remote-sensed enhanced vegetation index (EVI, Figure S2). For instance, if cells were identified as being in the latter two phenology stages, it was inferred that seeds were available because graminoid species typically produce seeds during plant maturity and the onset of yellowing.

2.3.3 | Model Building

To prevent spatiotemporal bias in quelea records impacting D-SDM performance, model weights proportional to survey effort were used to down weight contributions from records in over-sampled areas and vice versa. A proxy for survey effort was measured by the total number of e-Bird (Auer et al. 2022) records within a 100 km radius and within 14 days either side from each record. The selection of these buffer sizes was informed by qualitative assessments of avian regional sampling patterns in southern Africa, as documented in the literature (Reddy and Dávalos 2003) and supported by analysis of eBird data presented in Figures S3 and S4.

TABLE 1 | Dynamic and species-targeted explanatory variables incorporated into dynamic species distribution models for *Q. quelea* and associated datasets.

Type	Name	Description	Rationale	Dataset
Weather	8- and 52-week sum precipitation	Sum of rainfall in eight and 52 weeks prior (mm).	Eight weeks following sufficient rainfall, grass seed germinates (Ward 1971). Minimum annual rainfall required for germination (Cheke, Venn, and Jones 2007).	Karger et al. 2022
		8- and 52-week mean temperature and variability	Extreme temperatures may drive quelea occurrence (Elliott 1990).	
Resource	Water availability	Total 'water bodies' cells within accessible area.	Quelea require daily drinking surface water to persist (Jones 1989a).	Friedl and Sulla-Menashe 2019
	Tree availability	Total 'deciduous tree' cells within accessible area.	Quelea primarily breed in thorn trees but avoid forests (Ward 1971).	
	Habitat availability	Percentage cover of 'grassland', 'shrubland' and 'cereal cropland' within accessible area.	Suitable habitat availability predicts quelea occurrence (Ward 1971).	
	Seed abundance	Total grass and cereal crop seed available within accessible area.	Quelea consumes wild grass and cereal crop seed (Ward 1971).	

To establish a baseline understanding of SDM behaviour and tune model parameters for near-term hindcasting, we fitted two boosted regression tree models (BRTs) using all available data (2002–2016)—one for breeding and one for non-breeding records. We tested the model's ability to extrapolate over space and time using the block cross-validation method (Roberts et al. 2017), implemented through the 'dynamicSDM' R package (Dobson et al. 2023). Occurrence data were divided into sampling units, designated as non-contiguous sections of a terrestrial biome in southern Africa, and further split by year of record. Sampling units were then grouped into six blocks of approximately equal sample size, within each of which the mean and range of covariate data were similar. BRTs were fitted using a six-fold cross-validation approach, whereby each block was excluded in turn to be used as a testing dataset for models trained on the remaining five blocks of data. BRTs required parametrisation of the learning rate or 'shrinkage' parameter, which determines the contribution of each tree to the growing model. This parameterisation consisted of 'n.trees', the number of trees outcomes that are counted across, and tree complexity or 'interaction.depth', which controls the extent that interactions are fitted. Following Bagchi et al. (2013), these parameters were set respectively at 0.001, 5000, and complexity was varied between 1 and 4, selecting the value that minimised mean root mean square error (RMSE) across the six-fold cross validation block combination. In summary, we constructed one baseline model per season using tuned parameters, which were then used both to generate observed suitability maps for comparison with hindcast maps. Tuned parameters were then used to fit the hindcasting models (detailed in Section 2.4).

2.3.4 | Model Evaluation

Using the tuned model parameters, the performance of the breeding and non-breeding D-SDMs was measured by the area under the receiver operating characteristic curve (AUC), calculated based on the full dataset for training. AUC represents the model's ability to correctly discriminate a species presence from absence across all thresholds between 0 and 1. AUC values range from 0.5, indicating discrimination no better than random, to 1, indicating perfect discrimination. Percentage variable importance was quantified using the permute-after-calibration test (Breiman 2001), performed using the 'biomod2' R package (Thuiller et al. 2024). This method involves permuting each explanatory variable sequentially, thereby disrupting the relationship between the variable and D-SDM performance. The associated decrease in model performance quantifies that variable's importance to D-SDM predictive ability.

2.3.5 | Abundance-Suitability Relationship

To test whether projected distribution suitability was related to the abundance of quelea in each site, we extracted D-SDM explanatory variables for records collected by pest control organisations associated with quelea abundance estimates (Table S1). These explanatory variable values were used to predict occurrence probability using the baseline D-SDMs trained on all

available occurrence data. The linear relationship between quelea abundance and modelled distribution suitability was measured using Spearman's rank correlation as the abundance data were not normally distributed.

2.4 | Near-Term Hindcasting

2.4.1 | Overview of Approach

On the 1st of each month between 2004 and 2016, we generated seven-month near-term hindcasts of quelea distribution. Each hindcast is comprised of one distribution suitability map (0.05° spatial resolution) for every two-week period up to 7 months ahead, resulting in 14 maps per near-term hindcast. To create these maps, we generated seven-month near-term hindcasts of weather and resource explanatory variables (Section 2.4.2) across southern Africa, which were used by D-SDMs to project quelea occurrence probability. To align with quelea phenology, we projected breeding D-SDMs from December to May and non-breeding D-SDMs from June to November, clipping all projections to the quelea's known elevation range (0–1800 m, Jaeger, Erickson, and Jaeger 1979). We used two distinct approaches to fit the hindcasting D-SDMs to breeding and non-breeding datasets: "real-time" and "maximal". Real-time D-SDMs were fitted using all occurrence data available up until the hindcast initiation date. This approach allowed us to simulate real-world conditions, where predictions were made based solely on historical data leading up to the hindcast period. In contrast, maximal D-SDMs were fitted using all available data, excluding the respective hindcast period. By maximising the training dataset size, this approach allowed us to explore the potential benefits of increased data availability on hindcast accuracy and reliability. It also enabled examination of inter-annual variations in hindcast performance during extreme weather events, without the confounding effect of training dataset size. Hereafter, we refer to these two approaches as real-time and maximal. Finally, we evaluated the hindcast suitability maps generated by both maximal and real-time D-SDMs by comparing them to projections based on observed ecoclimatic conditions for the same period (Table 1), generated using baseline D-SDMs fitted to all available occurrence data (Section 2.3).

2.4.2 | Explanatory Variable Hindcasts

2.4.2.1 | Weather Variables. For every 2-week interval within each 7-month near-term hindcast period, 8- and 52-week weather variables (Table 1) were calculated by combining daily total precipitation and mean temperature from hindcast (7 months ahead of hindcast initiation) and historical datasets (up to 52 weeks prior to hindcast initiation). Hindcast weather data were extracted from the European Centre for Medium-Range Weather Forecasts (ECMWF) fifth generation seasonal forecast system (SEAS5) dataset at 1° spatial resolution (Johnson et al. 2019), comprising predictions by 25 ensemble members. SEAS5 releases seven-month near-term forecasts on the 1st of each month and also provides near-term hindcasts (or re-forecasts) for the 1st day of each month between 1981 and 2016. These hindcasts were generated with

a version of the forecast system closely aligned with that used for real-time forecasts, providing a good estimate of the bias and skill expected in the real-time forecasting system (Boas et al. 2023; Chevuturi et al. 2021). Historical weather data were extracted from the ECMWF atmospheric reanalysis of the global climate (ERA5) dataset at 0.25° spatial resolution (Hersbach et al. 2020). Whilst CHELSA-W5E5 historical weather data were used for D-SDM explanatory variables (Table 1), this dataset is not updated in real-time. Therefore, despite its coarser native resolution, we used the ERA5 dataset that is released at a 3-month lag from present day, because it offers more practical applicability for real-time forecasting.

The 3-month gap in ERA5 data from real-time was filled using values from the previous three SEAS5 forecasts at 1-month lead time, as forecasts match observed conditions well at such low lead times (Johnson et al. 2019).

To achieve a 0.05° spatial resolution and ensure these weather data were consistent with historical observations from the CHELSA-W5E5 dataset, we applied bias correction and spatial disaggregation techniques to ERA5 and SEAS5 data. Bias correction of near-term hindcasts was applied using CHELSA-W5E5 data aggregated to 1.0° (aligning with the spatial resolution of hindcasts) for empirical quantile mapping (EQM) in the ‘downscaleR’ R package (Bedia et al. 2020). EQM is a common technique that involves adjusting the cumulative distribution function of model data to match that of observational data (Cannon, Sobie, and Murdock 2015). This correction was applied separately for each variable, month, lead time, and ensemble member. Hindcasts from 1981 to 2001 were used to inform bias correction of hindcasts from 2002 to 2016. To achieve spatial disaggregation to a resolution of 0.05°, the widely used technique of spline interpolation (Lam 1983) was employed. The weather explanatory variables (Table 1) were calculated from the daily data using each of the 25 SEAS5 ensemble members separately, and the median value was then taken to produce deterministic forecasts (see Appendix A2 for comparison of the performance of individual ensemble members compared to the ensemble median).

2.4.2.2 | Resource Variables. As MODIS Annual Land Cover Type datasets are typically released with a 2-year lag from the present (Friedl and Sulla-Menashe 2019), we derived resource variable hindcasts using data from the dataset released two years prior. To hindcast seed abundance (Table 1), we employed a novel approach (see Appendix A3) that first involved classifying real-time vegetation growth stages in “cereal crop-land” and “grassland” land cover cells using 16-day MODIS EVI data (Table S2, Didan 2021). From this classification, the subsequent growth stages were extrapolated forward to each monthly interval within the 7-month hindcast, using average stage durations extracted from the historical dataset (Table 1). Using these hindcast growth stages, we calculated and inferred seed abundance using the same methodology applied to the historical dataset (Section 2.3.2).

2.4.2.3 | Evaluation. Explanatory variable Hindcasting skill was measured by the Pearson correlation between hindcast and observed remote-sensed variable data (Table 1) for each hindcast interval. A two-way ANOVA was used to

test for significant differences in this relationship across hindcast lead times and years and an interaction effect of variable type. ANOVAs were followed by post hoc Tukey’s HSD tests to look for significant pairwise differences across lead times years and variables.

2.4.3 | Distribution Suitability Hindcasts

2.4.3.1 | Hindcasting D-SDMs. For each hindcast period, real-time and maximal D-SDMs were fitted to their respective training datasets (Figure 1) using the tuned model parameters derived from the baseline D-SDMs (Section 2.3). D-SDM performance was measured using the AUC, based on predicted occurrence probabilities for occurrence records from the corresponding seven-month hindcast period (Figure 1). We used a two-way analysis of variance (ANOVA) to test for significant inter-annual variation in D-SDM performance, considering the factors of the year the D-SDM was generated and the type of dataset used for training, and their interaction effect. Post hoc Tukey’s honestly significant difference (HSD) test was used to look for significant pairwise differences between real-time and maximal D-SDM performances in each year.

2.4.3.2 | Hindcast Suitability and Evaluation. To generate hindcast distribution suitability maps for 14 intervals (once every 2 weeks) within each 7-month hindcast, hindcasting D-SDMs were applied to project suitability under hindcast ecoclimatic conditions across southern Africa (Figure 2). For evaluation, the baseline D-SDMs were applied to generate “observed” suitability maps based on observed ecoclimatic conditions for the corresponding period (Table 1). For example, the near-term hindcast initiated on 1 January 2008 generated 14 distribution suitability hindcasts between 2 weeks (14 January 2008) and 7 months ahead (1 August 2008). The two-week hindcast was compared to distribution suitability projected by the baseline D-SDMs using historical ecoclimatic data from 14 January 2008, and so on, once every 2 weeks up to 1 August 2008. Hindcast performance was measured by the Pearson correlation between observed and hindcast suitability in each cell. We used Kruskal–Wallis tests to assess significant differences in the median performance metrics across lead times and years, due to skewed data. Dunn’s post hoc test with Bonferroni correction was then applied for pairwise comparisons. Evaluation was repeated using distribution suitability projections from both real-time and maximal D-SDMs.

3 | Results

3.1 | Extreme Weather Events

On average, non-drought was experienced through much of the focal study period, with mild droughts also frequent (Figure S5a). Extreme drought events were rare, though most extensive and prolonged in 2005 and 2015 (Figure S5b). In 2005, extreme drought conditions were experienced for nine successive months from February to October, reaching a maximum extent of 37% of the *Quelea* range in June. In 2015, 9 months experienced extreme drought between January and December,

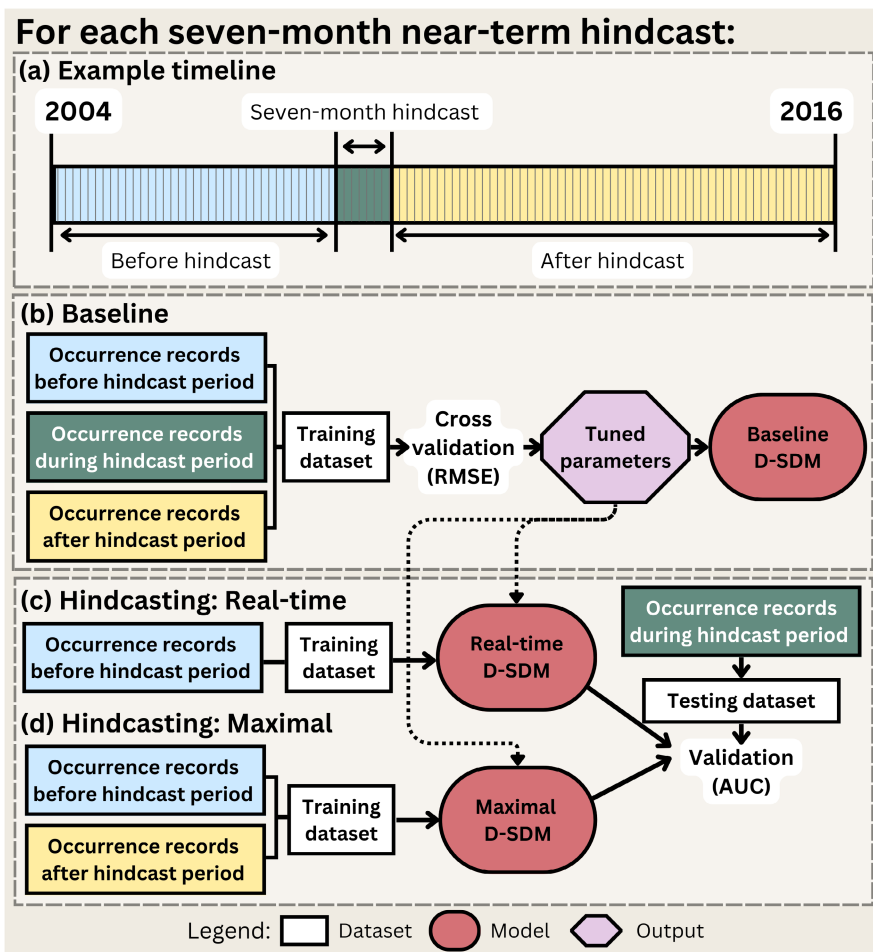


FIGURE 1 | Evaluation approach for near-term hindcast performance. (a) An example timeline illustrates the placement of a 7-month near-term hindcast within the study period 2004–2016. Hindcasts are initiated monthly (each grey line), spanning 7 months ahead from each initiation date. The green interval represents the current hindcast period and shifts to the right for each subsequent hindcast. This figure shows the use of occurrence records as training and testing datasets for generating and evaluating dynamic species distribution models (D-SDMs) used in hindcasting. The dotted lines represent the flow of output tuned parameters from one model being used as input parameters in other models. The solid lines represent a linkage in the flow of analysis from input dataset to output. (b) “Baseline”: D-SDM fitted using all available occurrence records from the study period. Model parameters were tuned through block cross-validation prior to achieving the final fitted “baseline” D-SDM. (c) “Real-time”: Hindcasting D-SDM fitted using only records available before the hindcast interval (blue period in the timeline), replicating data availability at that point. (d) “Maximal”: Hindcasting D-SDM fitted using occurrence records from both before and after the seven-month hindcast period (blue and yellow period in the timeline), allowing for an assessment of performance with increased training data availability. Hindcasting D-SDM performances were measured by AUC using occurrence records from within the seven-month hindcast period (green in the timeline).

interspersed between severe droughts, reaching a maximum extent of 16% in July.

3.2 | Species Distribution Modelling

3.2.1 | Baseline Models

Baseline D-SDMs were able to accurately explain the spatiotemporal patterns of quelea distribution in the breeding (AUC = 0.79, $N = 23,736$) and non-breeding seasons (AUC = 0.76, $N = 42,183$) as assessed on blocks that were quasi-independent from model fitting. On average, the most important ecoclimatic variables for explaining quelea breeding distribution were seed abundance (relative variable importance = 50%), 8-week mean temperature (20%), and 8-week total precipitation (14%, Table S3). Whereas, for non-breeding distribution,

the most important variables were seed abundance (40%), 52-week mean temperature (23%), and 8-week total precipitation (20%, Table S3). Removing the seed abundance explanatory variable from D-SDMs resulted in a decline in AUC by 6% and 7% observed across breeding and non-breeding models, respectively. A positive, albeit weak, statistically significant correlation was found between projected distribution suitability and quelea abundance (Spearman's rank correlation, $\rho = 0.18$, $p < 0.01$, $N = 4279$).

3.2.2 | Hindcasting Models

Throughout the study period, the hindcasting D-SDMs performed well in predicting quelea occurrences during the hindcast periods, with real-time training datasets (mean = 0.71, SD = 0.07, $N = 153$, Table S4) and maximal training datasets

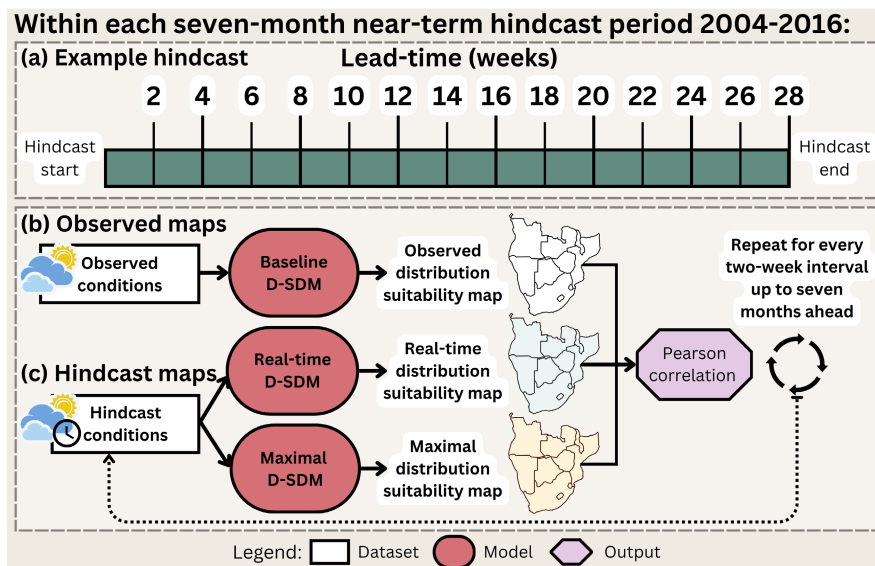


FIGURE 2 | Generation of near-term hindcast and observed distribution suitability maps for every 2-week interval within each 7-month near-term hindcast period. The timeline (a) depicts the intervals occurring once every 2 weeks within a 7-month seasonal hindcast at lead times from 2 to 28 weeks ahead; each line indicates when the maps were generated. This process was repeated at the start of every month from 2004 to 2016, aligning with the SEAS5 hindcast initiation dates. (b) Observed maps were generated by “baseline” D-SDM using observed ecoclimatic condition datasets for each 2-week interval. (c) Hindcast maps were generated by “real-time” and “maximal” D-SDMs using hindcast ecoclimatic conditions for each 2-week interval. The correlations between observed and hindcast suitability maps were calculated to measure hindcast performance at each lead time under varying training data constraints ($N=14$ per D-SDM type and hindcast period).

(mean = 0.74, SD = 0.05, $N=153$, Table S5). Nevertheless, we found significant inter-annual variation in hindcasting model performances (ANOVA, $F(12,298)=21.55$, $p<0.01$), which was significantly influenced by the interaction with D-SDM training dataset type (ANOVA, $F(1,298)=21.55$, $p<0.01$). Between 2005 and 2008, maximal D-SDMs performed significantly better than real-time D-SDMs (Figure S6, $p<0.01$). However, following 2009, when real-time D-SDM training dataset size reached ~3000 breeding and ~6000 non-breeding records, model performances were not significantly different between training dataset compositions (Figure S6 and Tables S4 and S5).

3.3 | Near-Term Hindcasting

3.3.1 | Real-Time Hindcasts

Quelea distribution hindcasts generated by real-time D-SDMs exhibited a moderate correlation with observed patterns of quelea distribution suitability across the 13-year period (median $r=0.61$, range = -0.31–0.89, $N=2184$, Table S6). There were significant differences in real-time hindcast performance across lead times and between years (Figure 3a, Kruskal-Wallis, $p<0.01$, Table S7). Performance was strongest between 2- and 4-week lead times ($R=0.72$), but still performed with good accuracy at longer lead times up to 12 weeks ahead (0.61–0.69, Table S8). Across all lead times, the correlation between observed and hindcast distribution suitability significantly increased over time ($r=0.84$, $p<0.01$), reaching an average of 0.80 in 2016 (Figure 3a). Real-time hindcasts were able to predict changes in environmental suitability for quelea under non-drought and extreme drought conditions (Figure 4). In this example, shown in Figure 4, real-time hindcasts anticipated the reduction in suitability compared to non-drought

conditions in the breeding season across southern Africa, with pronounced declines in northern South Africa, eastern Botswana, and southern Mozambique.

3.3.2 | Maximal Hindcasts

Quelea distribution hindcasts generated by maximal D-SDMs exhibited a strong correlation with observed patterns of quelea distribution suitability across the 13-year period (median $R=0.79$, range = -0.20–0.93, $N=2184$, Table S6). There were significant differences in maximal hindcast performance across lead times and between years (Figure 3b, Kruskal-Wallis, $p<0.01$, Table S7). Performance was strongest between 2- and 10-week lead times (R , 0.80–0.82), but still performed with high accuracy at longer lead times up to 28 weeks ahead (0.68–0.78, Table S8). Significant negative correlations with lead-time were found (-0.92, $p<0.01$), with median correlation declining by 17% from 0.82 to 0.68 between 2- and 28-week lead times (Table S8). Inter-annual pairwise comparisons revealed that the accuracy was significantly lower in 2005 and 2006 compared to several other years (Dunn's test, $p<0.01$, Table S9).

3.4 | Explanatory Variable Hindcasting Skill

Ecoclimatic variable hindcasts were strongly correlated with the observed, remote-sensed values (mean $r=0.89$, SD = 0.20, Table S10). On average, seed abundance was hindcast with the lowest skill (mean $r=0.42$, SD = 0.34) despite the strong accuracy of underlying models (80%–83%, Tables S11 and S12), followed by 8-week sum precipitation (mean $r=0.81$, SD = 0.08) and 52-week sum precipitation (mean $r=0.86$, SD = 0.04). Ecoclimatic

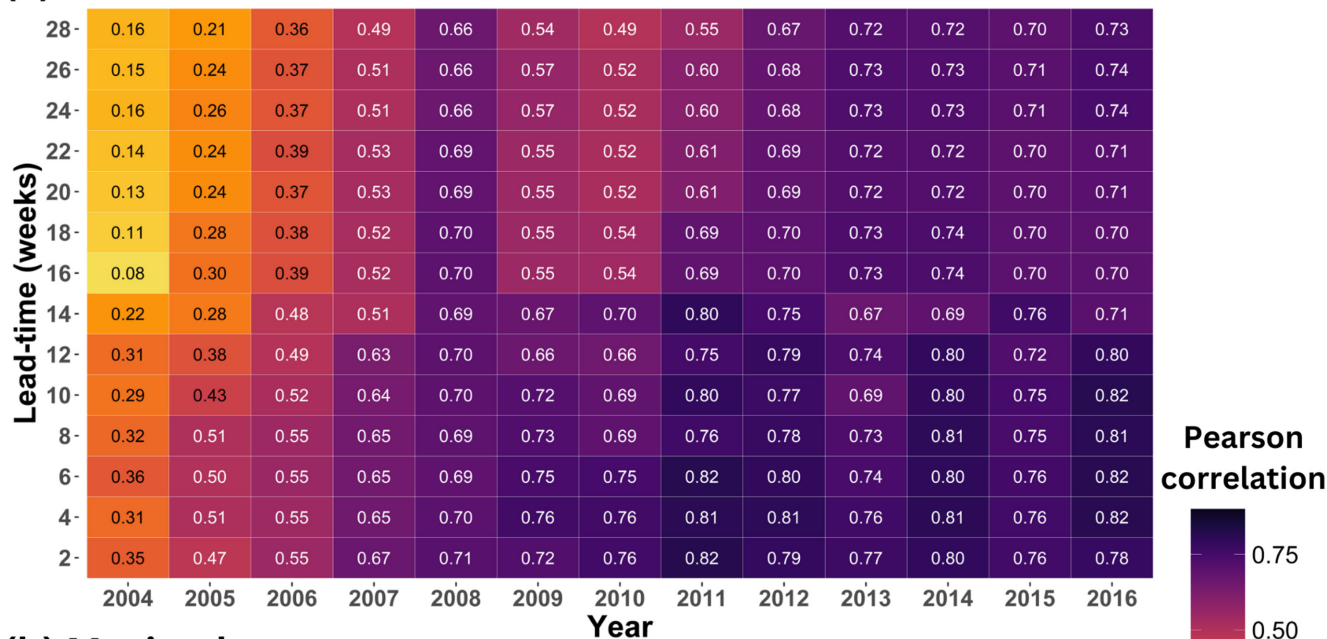
(a) Real-time**(b) Maximal**

FIGURE 3 | Median correlation between distribution suitability projections based on near-term hindcast and observed ecoclimatic conditions across lead times and years, generated through: (a) “real-time” technique that simulated real-time data availability, where projected D-SDMs were trained on all data available up until that respective hindcast’s initiation date; and (b) “maximal” technique, where D-SDMs projected onto hindcast ecoclimatic conditions were trained on all available training data from the study period but excluding from the respective hindcast’s period. All Pearson correlation tests were statistically significant ($p < 0.05$).

variable hindcasting skill varied significantly across lead times and between years (Figure 5, Tables S10 and S13). However, we found significant interaction effects of variable type (ANOVAs, $p < 0.01$, Tables S14 and 15), suggesting that the variation in hindcasting skill across lead times and between years was not consistent across variables. Ecoclimatic variable hindcasting skill was significantly negatively correlated with lead time ($r = -0.09$, $p < 0.01$). However, post hoc pairwise comparisons indicated that the significant differences in hindcasting skill between

lead-times were only observed in two variables (Tukey’s HSD, Table S16): seed abundance ($r = -0.70$, $p < 0.01$) and, less severely, in 8-week sum precipitation ($r = -0.16$, $p < 0.01$). Between years, post hoc pairwise comparisons revealed that only three variables showed significant inter-annual variations in hindcasting skill: significantly higher skill for seed abundance in 2016, and significantly lower skill for 8-week sum precipitation and 52-week precipitation in 2015 and 2016 (Tukey’s HSD, Table S17).

Near-term forecasts of mobile species distributions could anticipate changes under extreme weather events to inform more effective, adaptive management. Here, we demonstrate that distribution changes of a terrestrial mobile species during extreme weather events can be forecast accurately and at high spatiotemporal resolution, up to 7 months in advance. Robust D-SDM performances were driven by explanatory variables targeted to species ecology, suggesting that our approach could be readily applied to other species. Our results indicated that forecast uncertainty may be higher following extreme weather events, although we showed that additional training data could enhance performance. Overall, we found forecast accuracy was robust for providing timely warnings to decision-makers for adaptive management during extreme weather events.

4.1 | Forecast Utility for Adaptive Management

This study aimed to explore factors driving near-term distribution forecast uncertainty using hindcast data. We focused on the predictability of local weather phenomena and extreme events, as well as the influence of model structure and inputs. Our results showed that underlying ecoclimatic variables were consistently accurately hindcast throughout the study period, closely matching high-resolution observed conditions, with performance remaining stable even during extreme weather events. Consequently, we found that D-SDM training dataset size and composition had the largest impact on hindcast uncertainty. In general, as the training dataset grew, model performance increased, leading to closer alignment between projected and observed hindcast outputs. However, this effect plateaued after the dataset reached approximately 3000 breeding and 6000 non-breeding records (by 2009). Subsequently, the performances of real-time and maximal models converged, despite one using future data and the other relying solely on historical data. Maximal hindcasts were expected to consistently perform better due to their larger training dataset, which closely aligned with the baseline models' training datasets. However, the observed convergence in performances suggests that beyond a certain point, additional training data do not considerably enhance model learning or alter identified relationships. This presents an encouraging outlook for future forecasting efforts: while initial data scarcity may limit forecast accuracy, long-term monitoring could provide sufficient data to effectively inform management.

By employing the maximal hindcast approach, we explored inter-annual variations in hindcast performance across the study period, without the confounding effect of training dataset sizes increasing over time. This approach was supported by the convergence between real-time and maximal hindcasts once the historical dataset reached a sufficient size. In general, we observed strong performance of maximal D-SDMs across the study period, largely driven by the seed abundance explanatory variable, which represented the ephemeral availability of queleas' primary food. This followed expectations that incorporating explanatory variables that matched the drivers of quelea movements would enhance D-SDM performance (cf. Runge et al. 2015; Bateman, Vanderwal, and Johnson 2012; Burke et al. 2019; Kass et al. 2020). Nevertheless, despite

underlying variables also being consistently well-hindcasted, we observed a weaker relationship between projections by maximal D-SDMs and projections by baseline D-SDMs, during the extreme drought event of 2005/2006. The difference was that baseline D-SDMs were also trained on occurrence records from the hindcast periods during the extreme drought. This suggests that occurrence records from extreme weather events altered the modelled relationships. This could be due to quelea exhibiting novel occurrence-environment relationships in response to drought conditions (Elliott 1990). Consequently, although overall hindcast performance approaches an asymptote over time, we recommend that forecasters update D-SDMs as new conditions are experienced to capture these novel relationships and minimise forecast uncertainty during extreme weather events.

One benefit of near-term forecasting for adaptive management is the ability to have longer lead times to facilitate proactive (rather than reactive) decision-making (Dietze et al. 2018). Evaluating forecast accuracy at a lead time that is relevant for decision-making is therefore important. Lead times beyond which forecasts are not considered useful due to high uncertainty vary with target species and management aim. For example, in marine systems, lead times have been noted to range between two to four months (Eveson et al. 2015; Hobday et al. 2016), eight months (Malick et al. 2020) and twelve months (Brodie et al. 2023). For forecasting near-term blue whale *Balaenoptera musculus* distributions, to inform dynamic adjustment of industrial activities and protect foraging grounds, forecast accuracy at 3-week lead-time is critical (Barlow and Torres 2021). Whereas, for agronomic changes to manage yield loss to quelea, the forecast accuracy at lead times beyond one month is more relevant (Cheke, Venn, and Jones 2007). In southern Africa, planting decisions for wheat are normally made five months before this staple cereal crop is ready to harvest and becomes vulnerable to quelea damage (Elliott 1990). Here, we showed that quelea distribution could be forecast with strong accuracy up to seven months in advance; hence, our forecasts have high potential utility. Nevertheless, the accuracy of distribution hindcasts generated during and after the major drought of 2005 was notably lower at lead times beyond 14 weeks. Despite the relatively modest difference in accuracy, uncertainty may be increased at higher lead times during extreme events.

To inform management decisions effectively, near-term forecasts need to accurately anticipate species distributions at an appropriate spatial and temporal resolution. The required spatiotemporal resolution will vary with mobile species and management aim. For instance, higher resolution can benefit targeted conservation efforts, as seen in daily 0.01° forecasts for blue whale protection (Barlow and Torres 2021), while coarser resolutions, like monthly 1° forecasts of commercial fish for anglers, may prevent overexploitation (Brodie et al. 2017). In this study, we generated pest distribution forecasts at 0.05° spatial resolution and 2-week intervals up to seven months ahead, capturing local-scale distribution changes for highly targeted management. Targeting sites and times for management with high precision can prevent unnecessary or ineffective actions, maximising overall management efficiency. However, when generating high-resolution ecological

forecasts, there are associated trade-offs in computation time, data cost, and forecast uncertainty (Doblas-Reyes et al. 2013). Whilst open-source meteorological forecast datasets, which underpin ecological forecasts, are typically available at sub-daily temporal resolutions, spatial resolutions are relatively coarse, typically around 1° (Hudson et al. 2013; Johnson et al. 2019). Consequently, when ecological forecasting, empirical downscaling and spatial interpolation techniques are often employed to achieve higher spatial resolutions (Maraun and Widmann 2018; Hijmans et al. 2005). Yet, these derived meteorological forecasts may not capture small-scale phenomena and local-scale variations as accurately as a native high-resolution dataset. With technological advancements over time, we anticipate improved accessibility of such datasets, which will enable mobile species distributions to be forecast with even higher precision and accuracy for management.

Our forecasts provide stakeholders with dynamic estimates of environmental suitability for each grid cell, with higher values indicating a greater likelihood of species presence. Forecasts of species abundance could provide richer information on species population dynamics and associated impacts for informing management decisions (Howard et al. 2014; Kleiven et al. 2018). In theory, higher suitability values indicate areas where environmental conditions are more favourable for a mobile species and therefore, may harbour higher abundances (Vanderwal, Shoo, Johnson, and Williams 2009). Our results indicated a positive and significant relationship between suitability and abundance, as expected. However, the strength of this relationship was limited, likely due to different relationships between species abundance and the environment compared to species occurrence (Weber et al. 2017). Additionally, there were few mid-range points for evaluation due to standardised abundance records from pest control surveys typically recording either high pest abundance or absence. Future studies could train D-SDMs on abundance data to identify these relationships and forecast species abundance (Howard et al. 2014). Currently, for our study species, there is not sufficient data to train these relationships effectively for large-scale forecasting. For now, forecasts of distribution suitability serve as a strong proxy for anticipating impacts, particularly in agricultural areas where a high likelihood of occurrence indicates a considerable risk of pest influx.

Here, we generated near-term distribution forecasts of a highly mobile crop pest. Yet, this approach is widely applicable. Mobile species are found in diverse ecosystems worldwide and their movements can vary across a broad spectrum, from highly irregular and nomadic wandering in arid environments, to regular and seasonal migrations between continents (Teitelbaum and Mueller 2019; Alerstam, Hedenström, and Åkesson 2003). However, a shared characteristic among mobile species is that movements are driven by fluctuations in environmental conditions, including short-term weather conditions and resource availability (Jonzén et al. 2011), as individuals avoid poor conditions and seek suitable sites. Consequently, under extreme weather, mobile species often opt to, or find themselves compelled to, alter movement routes, destinations, and schedules, from mammals seeking alternative routes during extreme snowfall (Rosqvist, Inga, and Eriksson 2022), to migratory birds experiencing delayed arrival to breeding grounds during extreme drought (Tøttrup et al. 2012). Given our findings, we expect that

operational near-term forecasts could be generated for other mobile species requiring adaptive management by targeting D-SDM explanatory variables to that species' ecology. Near-term forecasts are available for diverse ecoclimatic variables that drive mobile species distributions (e.g., Copernicus Climate Change Service 2018). For instance, near-term forecasts of water availability and vegetation greening in Outback Australia could help forecast rare breeding events by ephemeral wetland species (Gentilli and Bekle 1983), whilst snow density and depth forecasts could be utilised for vulnerable mobile mammal species in the Arctic (Rosqvist, Inga, and Eriksson 2022).

4.2 | Management Implications Under Extreme Weather

Adaptive management of mobile organisms involves the implementation of transient action as their populations move across the landscape (Reynolds et al. 2017; Runge and Tulloch 2018). By anticipating distribution changes under extreme weather events, these dynamic actions can be proactive, which is expected to be more effective and cost-efficient than reactive actions (Dietze et al. 2018). Therefore, near-term distribution forecasts could more effectively mitigate the negative impacts associated with rapid and unforeseen changes in mobile species distributions under extreme weather—for instance, by preparing conservation measures for threatened mobile species (Runge et al. 2014; Boulton 2023), or preparing control of mobile pests and pathogens for vulnerable communities or ecosystems (Zhang et al. 2019). For adaptive management of quelea, our near-term forecasts could identify sites that are at high risk of pest occurrence during typical and extreme weather events to target control operations before crop damage occurs, or inform farmers of upcoming risks for agronomic management, including altering crop planting schedules or switching to crops that are less susceptible to damage. Such interventions could be more efficient than current practices at mitigating pest-driven yield loss during extreme drought events (Cheke and El Hady Sidatt 2019). The timely development of analogous strategies for other mobile species could prove critical to the mitigation of climate change impacts.

To implement near-term forecasts for adaptive management, forecast output must be accessible and comprehensible to relevant stakeholders (Dietze et al. 2018). This can be achieved using diverse methods (Hobday et al. 2016). The method chosen typically depends on the stakeholders of interest and sensitivity to the information, which could be particularly important when forecasting the distribution of vulnerable or overexploited mobile species (Brodie et al. 2017). Moreover, it is important that forecasts are communicated transparently with the level of uncertainty stated clearly for informed decision-making by stakeholders. Currently, there are many platforms available for freely developing and sharing code for near-term distribution forecasting, such as R (<https://www.r-project.org/>) and GitHub (<https://github.com/>). Such code could be automated using continuous integration tools (White et al. 2019), such as Travis CI (<https://www.travis-ci.com/>) and Docker Hub (<https://hub.docker.com/>). Indeed, this cyberinfrastructure could be utilised to iteratively and automatically update forecasting models with occurrence records as novel ecoclimatic conditions are

experienced under ongoing climate change, which, according to our results, is crucial to robust forecast performance. However, there are currently barriers to using such platforms, including the complexity of setting up iterative forecasting systems, and the limitations in computational resources without cost (White et al. 2019). Amidst growing demand for ecological forecasts as extreme weather events intensify worldwide, practical cyberinfrastructure and standardised approaches for sharing forecast output will need to become more available (Dietze et al. 2018).

5 | Conclusion

Looking ahead, we see great potential for near-term distribution forecasts to be developed and used for terrestrial mobile species, to better understand and manage species in dynamic systems amidst ongoing climate change. Such work will help to assess the generality and reproducibility of our findings from the current study. At the same time, we acknowledge the need for the development of practical cyberinfrastructure, to better integrate near-term forecasts into management frameworks for species. With extreme and novel weather conditions being increasingly experienced globally, managers need to account for the consequent forecast uncertainties when using such models to inform decision-making. Our work suggests that continually updating models with data that include contemporary extreme events will minimise these uncertainties. Overall, we anticipate that with advancing data availability over time, near-term distribution forecasts will become integral to the effective adaptive management of mobile species worldwide to mitigate impacts of extreme weather events.

Author Contributions

Rachel Dobson: conceptualization, formal analysis, methodology, writing – original draft, writing – review and editing. **Stephen G. Willis:** conceptualization, methodology, supervision, writing – review and editing. **Stewart Jennings:** conceptualization, methodology, supervision, writing – review and editing. **Robert A. Cheke:** conceptualization, methodology, supervision, writing – review and editing. **Andrew J. Challinor:** conceptualization, methodology, supervision, writing – review and editing. **Martin Dallimer:** conceptualization, funding acquisition, methodology, supervision, writing – review and editing.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are openly available in Zenodo at <https://doi.org/10.5281/zenodo.14001408> and GitHub at <https://github.com/r-a-dobson/seasonal-forecasting-quelea>. The occurrence data are available from the Global Biodiversity Information Facility (GBIF) at <https://doi.org/10.15468/aomfnb> and <https://doi.org/10.15468/dl.qza9ty>. The Standardized Precipitation-Evapotranspiration Index data are available from the Spanish National Research Council (CSIC) database at <https://doi.org/10.20350/digitalCSIC/16497>. The European Centre for Medium-Range Weather Forecasts (ECMWF) seasonal forecast daily and sub-daily data, as well as ECMWF Reanalysis Version 5 (ERA5) hourly data on single levels, are available from the Copernicus Climate Change Service (C3S) Climate Data Store (CDS) at <https://doi.org/>

[10.24381/cds.181d637e](https://doi.org/10.24381/cds.181d637e) and <https://doi.org/10.24381/cds.adbb2d47>, respectively. The Moderate Resolution Imaging Spectroradiometer (MODIS) Vegetation Indices, Land Cover Dynamics, and Land Cover Type data are available from NASA Earth Observing System Data and Information System (EOSDIS) Land Processes Distributed Active Archive Center (DAAC) at <https://doi.org/10.5067/MODIS/MOD13Q1.061>, <https://doi.org/10.5067/MODIS/MCD12Q2.061>, and <https://doi.org/10.5067/MODIS/MCD12Q1.061>, respectively. The Climatologies at High Resolution for the Earth's Land Surface Areas (CHELSA-W5E5) dataset is available from the Inter-Sectoral Impact Model Intercomparison Project Repository at <https://doi.org/10.48364/ISIMIP.836809>.

References

- Alerstam, T., A. Hedenström, and S. Åkesson. 2003. "Long-Distance Migration: Evolution and Determinants." *Oikos* 103, no. 2: 247–260.
- Auer, T., S. Barker, K. Borgmann, et al. 2022. *EOD-eBird Observation Dataset*. Occurrence dataset: Cornell Lab of Ornithology. <https://doi.org/10.15468/aomfnb> (Accessed via GBIF.org on 2021-07-21).
- Bagchi, R., M. Crosby, B. Huntley, et al. 2013. "Evaluating the Effectiveness of Conservation Site Networks Under Climate Change: Accounting for Uncertainty." *Global Change Biology* 19: 1236–1248.
- Barlow, D. R., and L. G. Torres. 2021. "Planning Ahead: Dynamic Models Forecast Blue Whale Distribution With Applications for Spatial Management." *Journal of Animal Ecology* 58: 2493–2504.
- Barnes, C. L., T. E. Essington, J. L. Pirtle, et al. 2022. "Climate-Informed Models Benefit Hindcasting but Present Challenges When Forecasting Species–Habitat Associations." *Ecography* 2022, no. 10: e06189.
- Bateman, B. L., J. Vanderwal, and C. N. Johnson. 2012. "Nice Weather for Bettongs: Using Weather Events, Not Climate Means, in Species Distribution Models." *Ecography* 35: 306–314.
- Bedia, J., J. Baño-Medina, M. N. Legasa, et al. 2020. "Statistical Downscaling With the downscaleR Package (v3. 1.0): Contribution to the VALUE Intercomparison Experiment." *Geoscientific Model Development* 13: 1711–1735.
- Beguèria, S., S. M. Vicente Serrano, F. Reig-Gracia, and B. Latorre Garcés. 2023. "SPEIbase v. 2.9 [Dataset]."
- Beguèria, S., S. M. Vicente-Serrano, F. Reig, and B. Latorre. 2014. "Standardized Precipitation Evapotranspiration Index (SPEI) Revisited: Parameter Fitting, Evapotranspiration Models, Tools, Datasets and Drought Monitoring." *International Journal of Climatology* 34: 3001–3023.
- BirdLife International. 2021. "Handbook of the Birds of the World." Bird Species Distribution Maps of the World Version 2021.1. <http://datazone.birdlife.org/species/requestdis>.
- Boas, T., H. R. Bogen, D. Ryu, H. Vereecken, A. Western, and H.-J. Hendricks Franssen. 2023. "Seasonal Soil Moisture and Crop Yield Prediction With Fifth-Generation Seasonal Forecasting System (SEAS5) Long-Range Meteorological Forecasts in a Land Surface Modelling Approach." *Hydrology Earth System Sciences* 27: 3143–3167.
- Boult, V. L. 2023. "Forecast-Based Action for Conservation." *Conservation Biology* 37: e14054.
- Breiman, L. 2001. "Random Forests." *Machine Learning* 45: 5–32.
- Brodie, S., A. J. Hobday, J. A. Smith, et al. 2017. "Seasonal Forecasting of Dolphin Distribution in Eastern Australia to Aid Recreational Fishers and Managers." *Deep Sea Research Part II: Topical Studies in Oceanography* 140: 222–229.
- Brodie, S., M. Pozo Buil, H. Welch, et al. 2023. "Ecological Forecasts for Marine Resource Management During Climate Extremes." *Nature Communications* 14: 7701.

- Bull, J. W., K. B. Suttle, N. J. Singh, and E. J. Milner-Gulland. 2013. "Conservation When Nothing Stands Still: Moving Targets and Biodiversity Offsets." *Frontiers in Ecology and the Environment* 11: 203–210.
- Burke, R. A., J. K. Frey, A. Ganguli, and K. E. Stoner. 2019. "Species Distribution Modelling Supports "Nectar Corridor" Hypothesis for Migratory Nectarivorous Bats and Conservation of Tropical Dry Forest." *Diversity and Distributions* 25: 1399–1415.
- Cannon, A. J., S. R. Sobie, and T. Q. Murdock. 2015. "Bias Correction of GCM Precipitation by Quantile Mapping: How Well Do Methods Preserve Changes in Quantiles and Extremes?" *Journal of Climate* 28: 6938–6959.
- Cheke, R. A., and M. El Hady Sidatt. 2019. "A Review of Alternatives to Fenthion for Quelea Bird Control." *Crop Protection* 116: 15–23.
- Cheke, R. A., J. F. Venn, and P. J. Jones. 2007. "Forecasting Suitable Breeding Conditions for the Red-Billed quelea *Quelea quelea* in Southern Africa." *Journal of Applied Ecology* 44: 523–533.
- Chevuturi, A., A. G. Turner, S. Johnson, et al. 2021. "Forecast Skill of the Indian Monsoon and Its Onset in the ECMWF Seasonal Forecasting System 5 (SEAS5)." *Climate Dynamics* 56: 2941–2957.
- Clark, N. J., T. Probst, G. Weerasinghe, and R. J. Soares Magalhães. 2022. "Near-Term Forecasting of Companion Animal Tick Paralysis Incidence: An Iterative Ensemble Model." *PLoS Computational Biology* 18: e1009874.
- Copernicus Climate Change Service, Climate Data Store. 2018. "Seasonal Forecast Daily and Subdaily Data on Single Levels." In *Copernicus Climate Change Service (C3S) Climate Data Store (CDS)*. Reading, UK: European Centre for Medium-Range Weather Forecasts. <https://doi.org/10.24381/cds.181d637e>.
- Craig, A. J. F. 2020. "Red-Billed Quelea (*Quelea quelea*), version 1.0." In *Birds of the World*, edited by J. del Hoyo, A. Elliott, J. Sargatal, D. A. Christie, and E. de Juana. Ithaca, NY, USA: Cornell Lab of Ornithology. <https://doi.org/10.2173/bow.rebque1.01>.
- Dean, W. R. J., P. Barnard, and M. D. Anderson. 2009. "When to Stay, When to Go: Trade-Offs for Southern African Arid-Zone Birds in Times of Drought." *South African Journal of Science* 105: 24–28.
- Didan, K. 2021. "MODIS/Terra Vegetation Indices 16-Day L3 Global 250m SIN Grid V061 [Data Set]." *NASA EOSDIS Land Processes DAAC*.
- Dietze, M. C., A. Fox, L. M. Beck-Johnson, et al. 2018. "Iterative Near-Term Ecological Forecasting: Needs, Opportunities, and Challenges." *Proceedings of the National Academy of Sciences* 115: 1424–1432.
- Diez, J. M., C. M. D'Antonio, J. S. Dukes, et al. 2012. "Will Extreme Climatic Events Facilitate Biological Invasions?" *Frontiers in Ecology and the Environment* 10: 249–257.
- Doblas-Reyes, F. J., J. García-Serrano, F. Lienert, A. P. Biescas, and L. R. L. Rodrigues. 2013. "Seasonal Climate Predictability and Forecasting: Status and Prospects." *WIREs Climate Change* 4: 245–268.
- Dobson, R., A. J. Challinor, R. A. Cheke, et al. 2023. "dynamicSDM: An R Package for Species Geographical Distribution and Abundance Modelling at High Spatiotemporal Resolution." *Methods in Ecology and Evolution* 14: 1190–1199.
- Dunn, D. C., S. M. Maxwell, A. M. Boustany, and P. N. Halpin. 2016. "Dynamic Ocean Management Increases the Efficiency and Efficacy of Fisheries Management." *Frontiers in Marine Science* 113: 668–673.
- Elith, J., M. Kearney, and S. Phillips. 2010. "The Art of Modelling Range-Shifting Species." *Methods in Ecology and Evolution* 1: 330–342.
- Elith, J., J. R. Leathwick, and T. Hastie. 2008. "A Working Guide to Boosted Regression Trees." *Journal of Animal Ecology* 77: 802–813.
- Elliott, C. 1990. "The Migrations of the Red-Billed Quelea *Quelea quelea* and Their Relation to Crop Damage." *Ibis* 132: 232–237.
- Eveson, J. P., A. J. Hobday, J. R. Hartog, C. M. Spillman, and K. M. Rough. 2015. "Seasonal Forecasting of Tuna Habitat in the Great Australian Bight." *Fisheries Research* 170: 39–49.
- FAO, ECA, and AUC. 2020. "Africa Regional Overview of Food Security and Nutrition 2019." <https://doi.org/10.4060/CA7343EN>. Accra.
- Friedl, M., J. Gray, and D. Sulla-Menashe. 2019. "MCD12Q2 MODIS/Terra+Aqua Land Cover Dynamics Yearly L3 Global 500m SIN Grid V006 [Data Set]." *NASA EOSDIS Land Processes DAAC*.
- Friedl, M., and D. Sulla-Menashe. 2019. "MCD12Q1 MODIS/Terra+Aqua Land Cover Type Yearly L3 Global 500m SIN Grid V006 [MCD12Q1]." *NASA EOSDIS Land Processes DAAC*.
- GBIF Occurrence Download. 2021. <https://doi.org/10.15468/dl.qza9ty>.
- Gentilli, J., and H. Bekle. 1983. "Modelling a Climatically Pulsating Population: Grey Teal in South-Western Australia." *Journal of Biogeography* 10: 75–96.
- Guisan, A., and W. Thuiller. 2005. "Predicting Species Distribution: Offering More Than Simple Habitat Models." *Ecology Letters* 8: 993–1009.
- Haines, A., R. S. Kovats, D. Campbell-Lendrum, and C. Corvalán. 2006. "Climate Change and Human Health: Impacts, Vulnerability, and Mitigation." *Lancet* 367: 2101–2109.
- Hersbach, H., B. Bell, P. Berrisford, et al. 2020. "The ERA5 Global Reanalysis." *Quarterly Journal of the Royal Meteorological Society* 146: 1999–2049.
- Hijmans, R. J., S. E. Cameron, J. L. Parra, P. G. Jones, and A. Jarvis. 2005. "Very High Resolution Interpolated Climate Surfaces for Global Land Areas." *International Journal of Climatology: A Journal of the Royal Meteorological Society* 25: 1965–1978.
- Hobday, A. J., C. M. Spillman, J. P. Eveson, and J. R. Hartog. 2016. "Seasonal Forecasting for Decision Support in Marine Fisheries and Aquaculture." *Fisheries Oceanography* 25: 45–56.
- Howard, C., P. A. Stephens, J. W. Pearce-Higgins, R. D. Gregory, and S. G. Willis. 2014. "Improving Species Distribution Models: The Value of Data on Abundance." *Methods in Ecology and Evolution* 5: 506–513.
- Hudson, D., A. G. Marshall, Y. Yin, O. Alves, and H. H. Hendon. 2013. "Improving Intraseasonal Prediction With a New Ensemble Generation Strategy." *Monthly Weather Review* 141: 4429–4449.
- Jaeger, M. M., R. L. Bruggers, and W. A. Erickson. 1989. "Formation, Sizes, and Groupings of Quelea Nesting Colonies." In *Quelea quelea: Africa's bird pest*, edited by R. Bruggers and C. Elliott, 181–197. Oxford, England: Oxford University Press.
- Jaeger, M. M., W. A. Erickson, and M. E. Jaeger. 1979. "Sexual Segregation of Red-Billed Queleas (*Quelea quelea*) in the Awash River Basin of Ethiopia." *Auk* 96: 516–524.
- Johnson, S. J., T. N. Stockdale, L. Ferranti, et al. 2019. "SEAS5: The New ECMWF Seasonal Forecast System." *Geoscientific Model Development* 12: 1087–1117.
- Jones, P. J. 1989a. "Distribution, Populations, and Migration Patterns of Quelea in Southern Africa." In *Quelea quelea: Africa's bird pest*, edited by R. Bruggers and C. Elliott, 132–143. Oxford, England: Oxford University Press.
- Jones, P. J. 1989b. "Factors Determining the Breeding Season and Clutch Size." In *Quelea quelea: Africa's bird pest*, edited by R. Bruggers and C. H. Elliot. Oxford, UK: Oxford University Press.
- Jonzén, N., E. Knudsen, R. D. Holt, and B. E. Sæther. 2011. "Uncertainty and Predictability: The Niches of Migrants and Nomads." In *Animal Migration: A Synthesis*, 91–109. Oxford, UK: Oxford University Press.
- Karger, D. N., S. Lange, C. Hari, et al. 2022. "CHELSA-W5E5: Daily 1 Km Meteorological Forcing Data for Climate Impact Studies." *Earth System Science Data Discussions* 2022: 1–28.

- Kass, J. M., R. P. Anderson, A. Espinosa-Lucas, et al. 2020. "Biotic Predictors With Phenological Information Improve Range Estimates for Migrating Monarch Butterflies in Mexico." *Ecography* 43: 341–352.
- Kell, L. T., A. Kimoto, and T. Kitakado. 2016. "Evaluation of the Prediction Skill of Stock Assessment Using Hindcasting." *Fisheries Research* 183: 119–127.
- Kleiven, E. F., J.-A. Henden, R. A. Ims, and N. G. Yoccoz. 2018. "Seasonal Difference in Temporal Transferability of an Ecological Model: Near-Term Predictions of Lemming Outbreak Abundances." *Scientific Reports* 8: 15252.
- Knox, J., T. Hess, A. Daccache, and T. Wheeler. 2012. "Climate Change Impacts on Crop Productivity in Africa and South Asia." *Environmental Research Letters* 7: 034032.
- Lam, N. S.-N. 1983. "Spatial Interpolation Methods: A Review." *American Cartographer* 10: 129–150.
- López-Hoffman, L., C. C. Chester, D. J. Semmens, et al. 2017. "Ecosystem Services From Transborder Migratory Species: Implications for Conservation Governance." *Annual Review of Environment and Resources* 42: 509–539.
- Malick, M. J., S. A. Siedlecki, E. L. Norton, et al. 2020. "Environmentally Driven Seasonal Forecasts of Pacific Hake Distribution." *Frontiers in Marine Science* 7: 578490.
- Maraun, D., and M. Widmann. 2018. *Statistical Downscaling and Bias Correction for Climate Research*. Cambridge, UK: Cambridge University Press.
- Maxwell, S. L., N. Butt, M. Maron, et al. 2019. "Conservation Implications of Ecological Responses to Extreme Weather and Climate Events." *Diversity and Distributions* 25: 613–625.
- McKechnie, A. E., P. A. Hockey, and B. O. Wolf. 2012. "Feeling the Heat: Australian Landbirds and Climate Change." *Emu-Austral Ornithology* 112: i–vii.
- McKee, T. B., N. J. Doesken, and J. Kleist. 1993. "The Relationship of Drought Frequency and Duration to Time Scales." In *Proceedings of the 8th Conference on Applied Climatology*, vol. 17, 179–183. Boston, Massachusetts, USA: American Meteorological Society.
- McWilliam, A., and R. Cheke. 2004. "A Review of the Impacts of Control Operations Against the Red-Billed quelea (*Quelea quelea*) on Non-Target Organisms." *Environmental Conservation* 31: 130–137.
- Milanesi, P., F. Della Rocca, and R. A. Robinson. 2020. "Integrating Dynamic Environmental Predictors and Species Occurrences: Toward True Dynamic Species Distribution Models." *Ecology and Evolution* 10: 1087–1092.
- Muhling, B. A., S. Brodie, J. A. Smith, et al. 2020. "Predictability of Species Distributions Deteriorates Under Novel Environmental Conditions in the California Current System." *Frontiers in Marine Science* 7: 589.
- Murali, G., T. Iwamura, S. Meiri, and U. Roll. 2023. "Future Temperature Extremes Threaten Land Vertebrates." *Nature* 615: 461–467.
- Nakagawa, S., and R. P. Freckleton. 2008. "Missing Inaction: The Dangers of Ignoring Missing Data." *Trends in Ecology & Evolution* 23: 592–596.
- Nandintsetseg, D., C. Bracis, K. A. Olson, et al. 2019. "Challenges in the Conservation of Wide-Ranging Nomadic Species." *Journal of Applied Ecology* 56: 1916–1926.
- New, M., D. Reckien, D. Viner, et al. 2022. "Decision-Making Options for Managing Risk." In *Climate Change 2022: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, edited by H.-O. Pörtner, D. C. Roberts, M. Tignor, et al., 2539–2654. Cambridge, UK: Cambridge University Press.
- Niang, I., O. C. Ruppel, M. A. Abdrabo, et al. 2014. "Africa." In *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part B: Regional Aspects*. Cambridge, UK: Cambridge University Press.
- O'Kane, C. 2024. "Continental Europe Has New Hottest Day on Record at Nearly 120°F in Sicily." *CBS News*.
- Poynting, M. 2024. "Amazon's Record Drought Driven by Climate Change." *BBC News, January*.
- Prugh, L. R., N. Deguines, J. B. Grinath, et al. 2018. "Ecological Winners and Losers of Extreme Drought in California." *Nature Climate Change* 8: 819–824.
- Reddy, S., and L. M. Dávalos. 2003. "Geographical Sampling Bias and Its Implications for Conservation Priorities in Africa." *Journal of Biogeography* 30: 1719–1727.
- Reynolds, M. D., B. L. Sullivan, E. Hallstein, et al. 2017. "Dynamic Conservation for Migratory Species." *Science Advances* 3: e1700707.
- Roberts, D. R., V. Bahn, S. Ciuti, et al. 2017. "Cross-Validation Strategies for Data With Temporal, Spatial, Hierarchical, or Phylogenetic Structure." *Ecography* 40: 913–929.
- Rodenburg, J., M. Demont, A. Sow, and I. Dieng. 2014. "Bird, Weed and Interaction Effects on Yield of Irrigated Lowland Rice." *Crop Protection* 66: 46–52.
- Rosqvist, G. C., N. Inga, and P. Eriksson. 2022. "Impacts of Climate Warming on Reindeer Herding Require New Land-Use Strategies." *Ambio* 51: 1247–1262.
- Runge, C., and A. I. T. Tulloch. 2018. "Solving Problems of Conservation Inadequacy for Nomadic Birds." *Australian Zoologist* 39: 280–295.
- Runge, C. A., T. G. Martin, H. P. Possingham, S. G. Willis, and R. A. Fuller. 2014. "Conserving Mobile Species." *Frontiers in Ecology and the Environment* 12: 395–402.
- Runge, C. A., A. Tulloch, E. Hammill, H. P. Possingham, and R. A. Fuller. 2015. "Geographic Range Size and Extinction Risk Assessment in Nomadic Species." *Conservation Biology* 29: 865–876.
- Seneviratne, S. I., X. Zhang, M. Adnan, et al. 2021. "Weather and Climate Extreme Events in a Changing Climate." In *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, edited by V. Masson-Delmotte, P. Zhai, A. Pirani, et al., 1513–1766. Cambridge, UK: Cambridge University Press.
- Slingo, J. M., A. J. Challinor, B. J. Hoskins, and T. R. Wheeler. 2005. "Introduction: Food Crops in a Changing Climate." *Philosophical Transactions of the Royal Society, B: Biological Sciences* 360: 1983–1989.
- Sutherst, R. W., F. Constable, K. J. Finlay, R. Harrington, J. Luck, and M. P. Zalucki. 2011. "Adapting to Crop Pest and Pathogen Risks Under a Changing Climate." *WIREs Climate Change* 2: 220–237.
- Teitelbaum, C. S., and T. Mueller. 2019. "Beyond Migration: Causes and Consequences of Nomadic Animal Movements." *Trends in Ecology & Evolution* 34: 569–581.
- Thuiller, W., D. Georges, M. Gueguen, et al. 2024. "biomod2: Ensemble Platform for Species Distribution Modeling (Version 4.2–6-1)." [R package]. <https://biomodhub.github.io/biomod2/>.
- Tøttrup, A. P., R. H. Klaassen, M. W. Kristensen, et al. 2012. "Drought in Africa Caused Delayed Arrival of European Songbirds." *Science* 338: 1307.
- Tulloch, A. I. T., V. Hagger, and A. C. Greenville. 2020. "Ecological Forecasts to Inform Near-Term Management of Threats to Biodiversity." *Global Change Biology* 26: 5816–5828.
- Ummenhofer, C. C., and G. A. Meehl. 2017. "Extreme Weather and Climate Events With Ecological Relevance: A Review." *Philosophical Transactions of the Royal Society B* 372: 20160135.

- Vanderwal, J., L. P. Shoo, C. Graham, and S. E. Williams. 2009. "Selecting Pseudo-Absence Data for Presence-Only Distribution Modeling: How Far Should You Stray From What You Know?" *Ecological Modelling* 220: 589–594.
- Vanderwal, J., L. P. Shoo, C. N. Johnson, and S. Williams. 2009. "Abundance and the Environmental Niche: Environmental Suitability Estimated From Niche Models Predicts the Upper Limit of Local Abundance." *American Naturalist* 174: 282–291.
- Visser, M. E. 2008. "Keeping Up With a Warming World; Assessing the Rate of Adaptation to Climate Change." *Proceedings of the Royal Society B: Biological Sciences* 275: 649–659.
- Walsh, J. C., J. E. Pendray, S. C. Godwin, et al. 2020. "Relationships Between Pacific Salmon and Aquatic and Terrestrial Ecosystems: Implications for Ecosystem-Based Management." *Ecology* 101: e03060.
- Ward, P. 1971. "The Migration Patterns of *Quelea quelea* in Africa." *Ibis* 113: 275–297.
- Weber, M. M., R. D. Stevens, J. A. F. Diniz-Filho, and C. E. V. Grelle. 2017. "Is There a Correlation Between Abundance and Environmental Suitability Derived From Ecological Niche Modelling? A Meta-Analysis." *Ecography* 40: 817–882.
- White, E. P., G. M. Yenni, S. D. Taylor, et al. 2019. "Developing an Automated Iterative Near-Term Forecasting System for an Ecological Study." *Methods in Ecology and Evolution* 10: 332–344.
- Wiley, J. W., and J. M. Wunderle. 1993. "The Effects of Hurricanes on Birds, With Special Reference to Caribbean Islands." *Bird Conservation International* 3: 319–349.
- Woelmer, W. M., R. Q. Thomas, M. E. Lofton, R. P. McClure, H. L. Wander, and C. C. Carey. 2022. "Near-Term Phytoplankton Forecasts Reveal the Effects of Model Time Step and Forecast Horizon on Predictability." *Ecological Applications* 32, no. 7: e2642.
- Zhang, L., M. Lecoq, A. Latchininsky, and D. M. Hunter. 2019. "Locust and Grasshopper Management." *Annual Review of Entomology* 64: 15–34.
- Zimmermann, N. E., T. C. Edwards Jr., C. H. Graham, P. B. Pearman, and J.-C. Svenning. 2010. "New Trends in Species Distribution Modelling." *Ecography* 33: 985–989.

Supporting Information

Additional supporting information can be found online in the Supporting Information section.