RESEARCH ARTICLE

Evaluation and validation of TAMSAT-ALERT soil moisture and WRSI for use in drought anticipatory action

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Funding information
Bill and Melinda Gates Foundation; Natural Environment Research Council, Grant/Award Numbers: NE/P000673/1, NE/R000034/1, NE/R014116/1, NE/R014272/1

Abstract

Reliable information on the likelihood of drought is of crucial importance in agricultural planning and humanitarian decision-making. Acting based upon probabilistic forecasts of drought, rather than responding to prevailing drought conditions, has the potential to save lives, livelihoods and resources, but is accompanied by the risk of acting in vain. The suitability of a novel forecasting tool is assessed in the present paper in terms of its ability to provide skilful information of the likelihood of drought impacts on crops and pasture within a timeframe that allows for anticipatory action. The Tropical Applications of Meteorology using SATellite data—AgriculturaL Early waRning sysTem (TAMSAT-ALERT) tool provides forecasts of seasonal mean soil moisture and the water requirement satisfaction index (WRSI). TAMSAT-ALERT metrics were found to be strongly correlated with pasture availability and maize yield in Kenya and provided skilful forecasts early in key seasons, allowing sufficient time for preparatory actions. Incorporating TAMSAT-ALERT forecasts in a layered approach, with actions triggered by spatiotemporally varying triggers and fundamentally informed by humanitarian actors, will provide reliable information on the likelihood of drought, ultimately mitigating food insecurity.

KEYWORDS

anticipatory action, drought, soil moisture, TAMSAT-ALERT, validation, WRSI

1 | INTRODUCTION

For millions of farmers across Africa, accurate and timely information on the likelihood of drought is of crucial importance for farming decisions. The need for such information is exacerbated given that irrigation across the continent is limited (You *et al*., 2011; Burney *et al*., 2013; Nakawuka *et al*., 2018), such that farmers rely heavily on seasonal rainfall to support crop and pasture production. Reliable information on drought can, therefore, inform decisions about when to prepare land, plant and harvest, which variety of seeds to plant, how best to

manage grazing resources, and post-harvest decisions regarding selling and storage.

Drought information is also of high priority for humanitarian aid organizations, as droughts often result in losses to livelihoods and food insecurity for vulnerable communities. At the same time, it is increasingly recognized that humanitarian actions made in anticipation of drought more effectively reduce the impacts, protecting lives and livelihoods whilst sparing limited resources (Braman *et al.*, 2013). To that end, many humanitarian organizations are moving towards anticipatory risk-management approaches to drought: Rather than acting in response to ensuing drought conditions, actions are taken based upon probabilistic forecasts of drought.

Anticipatory drought-management approaches define triggers that are used to activate early actions before a drought event occurs and the impacts are realized. These approaches make use of existing risk information collected by drought early warning systems (DEWS) and integrate forecasts of drought-relevant metrics such that early warnings are not based solely on observations, but consider the potential future evolution of drought risk and impact. Actions are, therefore, anticipatory, with an emphasis on mitigating risks.

The Red Cross Climate Centre recently outlined a suite of anticipatory actions to mitigate the impacts of drought (Heinrich and Bailey, 2020). For example, cash transfers to individuals, households or communities allow those at risk to purchase food items, rehabilitate water storage facilities or avoid adopting negative coping strategies such as destocking; the distribution of water storage equipment, rehabilitation of boreholes and sensitization around good water-management practices can alleviate strain on limited water supplies; since some diseases are closely linked to drought, the distribution of health services (such as vaccinations for people and livestock, water-purification tablets and awareness raising) can reduce the spread of disease; and actions directly targeting food insecurity might include the distribution of livestock fodder, fertilizer and farming equipment, or the provision of drought-tolerant seeds. Each possible action has an associated timeframe in which its deployment will be most effective (Coughlan De Perez *et al.*, 2015). Distribution of drought-tolerant seeds, for example, is only effective if actioned ahead of the season, before farmers begin to plant. Other actions, including cash transfers, health services and distribution of fodder, remain effective if issued part way through the growing season.

Anticipatory approaches to drought management are currently receiving considerable investment given their potential to improve food security, safeguard human well-being and stabilize economies (Cabot Venton *et al.*, 2012; Hillier and Dempsey, 2012; Coughlan De Perez *et al.*, 2015; UNICEF and WFP, 2015). Some initiatives currently underway include the Red Cross's Forecast-Based Action Early Action Protocols (IFRC, 2020), the World Food Programme's FoodSECuRE approach (WFP, 2018), the Food and Agriculture Organization's Early-Warning Early-Action programme (FAO, 2016), the START Network's Drought Financing Facility (START Network, 2017), and the World Bank's Famine Action Mechanism (The World Bank, 2020). However, major challenges remain in developing operational drought forecasts that reliably predict the location, magnitude and impacts of drought.

In order to support an anticipatory approach to drought management successfully, operational drought forecasts must: (1) forecast a metric relevant to the impacts of drought; (2) provide skilful predictions of drought within a timeframe that allows actions to take place; and (3) include skill information on drought forecasts to build users' confidence and encourage a long-term perspective (Cash *et al.*, 2003; Lemos *et al.*, 2012; Coughlan De Perez *et al.*, 2015). Anticipatory systems also need to factor in the slow evolution of drought, and the need for different actions and responses as drought develops.

Several approaches have already been developed. Shukla *et al.* (2014) describe the forecasting system used by the Famine Early Warning Systems Network (FEWSNET) to assess seasonal agricultural production in East Africa. The system uses meteorological variables to drive the variable infiltration capacity (VIC) hydrological model, providing an ensemble forecast of soil moisture. The ensemble is then weighted using the Climate Forecasts System Version 2 precipitation forecast. Manatsa *et al.* (2011) use the FAO's AgrometShell software, containing an agrometeorological water-balance model, to estimate seasonal crop water requirement satisfaction and yield. Similarly, Hansen *et al.* (2004) combine a global circulation model-based seasonal rainfall forecast with a wheat-simulation model to provide probabilistic regional wheat yield forecasts for Queensland, Australia.

Here, we assess the suitability of a complementary drought-forecasting tool to provide a trigger for anticipatory drought management in Sub-Saharan Africa. The Tropical Applications of Meteorology using SATellite data—AgriculturaL Early waRning sysTem (TAMSAT-ALERT) (abbreviated to T-A) is a decision-support tool that aims to provide early warnings of drought by exploiting the expected persistence of root-zone soil moisture anomalies (Brown *et al.*, 2017).

Soil moisture is directly relevant to agricultural drought, a major precursor of food insecurity (Panu and Sharma, 2002; Baik *et al.*, 2019). Whilst obviously relevant, soil moisture information is limited. Field observations of

soil moisture across Sub-Saharan Africa are inadequate for operational purposes (Myeni *et al.*, 2019). In addition, modelling approaches to estimate soil moisture exhibit large sensitivities to land-surface properties, parameterizations and meteorological forcing data (Brocca *et al.*, 2017). The T-A system uses components from a land-surface model driven by observed rainfall and forced with the meteorological forecast. The ability of T-A to model soil moisture accurately therefore warrants the validation carried out in the present study.

T-A provides daily estimates of soil moisture and the water requirement satisfaction index (WRSI) (Doorenbos and Pruitt, 1977). The WRSI is the ratio of cumulative actual crop evapotranspiration to the cumulative potential evapotranspiration over a certain growing period (Senay and Verdin, 2003). It describes how much water is available for plants to grow without water stress, and its value ranges from 0 to 100, where 100 indicates no water stress and 0 indicates complete dryness. The WRSI is calculated using:

$$WRSI = \left(\frac{\sum_{t=1}^{t} ET_t}{\sum_{t=1}^{t} PET_t} \right) \times 100$$

where *t* is the time period; ET_t is the actual evapotranspiration of the crop for time *t*; and PET_t is the potential evapotranspiration of the crop for time *t*. T-A soil moisture and WRSI are available for all Africa at a 0.25° resolution. The historic data sets begin in 1983, when the TAMSAT rainfall archive began (Maidment *et al.*, 2017). Alongside the historic data set, T-A importantly includes a forecasting system to predict soil moisture and the WRSI for a region and period of interest (Asfaw *et al.*, 2018). In principle, T-A estimates of the WRSI and soil moisture can be updated throughout the season, and continually updated bulletins based on T-A forecasts are already operational in several regions of West and East Africa.

The T-A forecasting system presents promise for use in anticipatory drought-management protocols. In comparison with rainfall, soil moisture is more directly relevant to agricultural drought and is therefore more likely to relate to the impacts of drought, including crop yield and pasture availability, and ultimately food security outcomes (Enenkel *et al.*, 2015). Moreover, T-A soil moisture and WRSI data can be produced in near real time, making them suitable for operational purposes. However, two important aspects of T-A must be assessed to determine its suitability for anticipatory drought management, which are addressed in the present paper:

- The relationship between T-A soil moisture/WRSI and independent drought-impact metrics must be

established. For example, in recent surveys conducted by the Kenyan Red Cross, participants identified water scarcity, reduced crop yield and lack of pasture as the primary impacts of drought. Given that crop yield and pasture availability directly underpin food security and are, at least in part, determined by water scarcity, we decided to use measures of crop yield and pasture availability to evaluate the relevance of T-A for drought management.

- In order to provide useful early warnings, T-A must be able to anticipate drought reliably with enough lead-time to allow appropriate early actions to take place. A sufficient lead-time should allow for stakeholders involved in drought management to release funds, identify priority areas and implement actions. Consideration must be given to the timeframe in which actions are most effective, and the time required to implement different types of actions, which in part depends on the operational capacity of the institutions involved. To address this, we generated T-A hindcasts at a range of lead-times and examined their skill in predicting the seasonal soil moisture, WRSI and drought-impacts.

Results are discussed in relation to anticipatory drought-management approaches, and suggestions are made for realizing the use of T-A forecasts to mitigate the impacts of drought.

1.1 | Study region

The study focuses on maize cultivation and pasture availability in Kenya, where maize provides a staple source of food for a large proportion of the population (Djurfeldt and Wambugu, 2011). In addition, Kenya has a large pastoral community (Kratli and Swift, 2014; FAO, 2018) that depends on the available pasture to support livestock. Agricultural systems in Kenya are predominantly rainfed, and so crop and pasture production are largely constrained to the rainy seasons (Figure 1).

T-A soil moisture and WRSI estimates and forecasts were evaluated for the two key growing seasons in Kenya: the long rains (March–May) and the short rains (October–December) (Figure 1). Whilst drought threatens the livelihoods and lives of communities across Africa, we chose to focus the study on Kenya, where efforts are already underway to establish anticipatory drought-management protocols. Comparing the two growing seasons in Kenya will provide a useful insight into the suitability of T-A for drought management in a range of situations. Across most of Kenya, the March–May long rains are considered the major growing season, but in
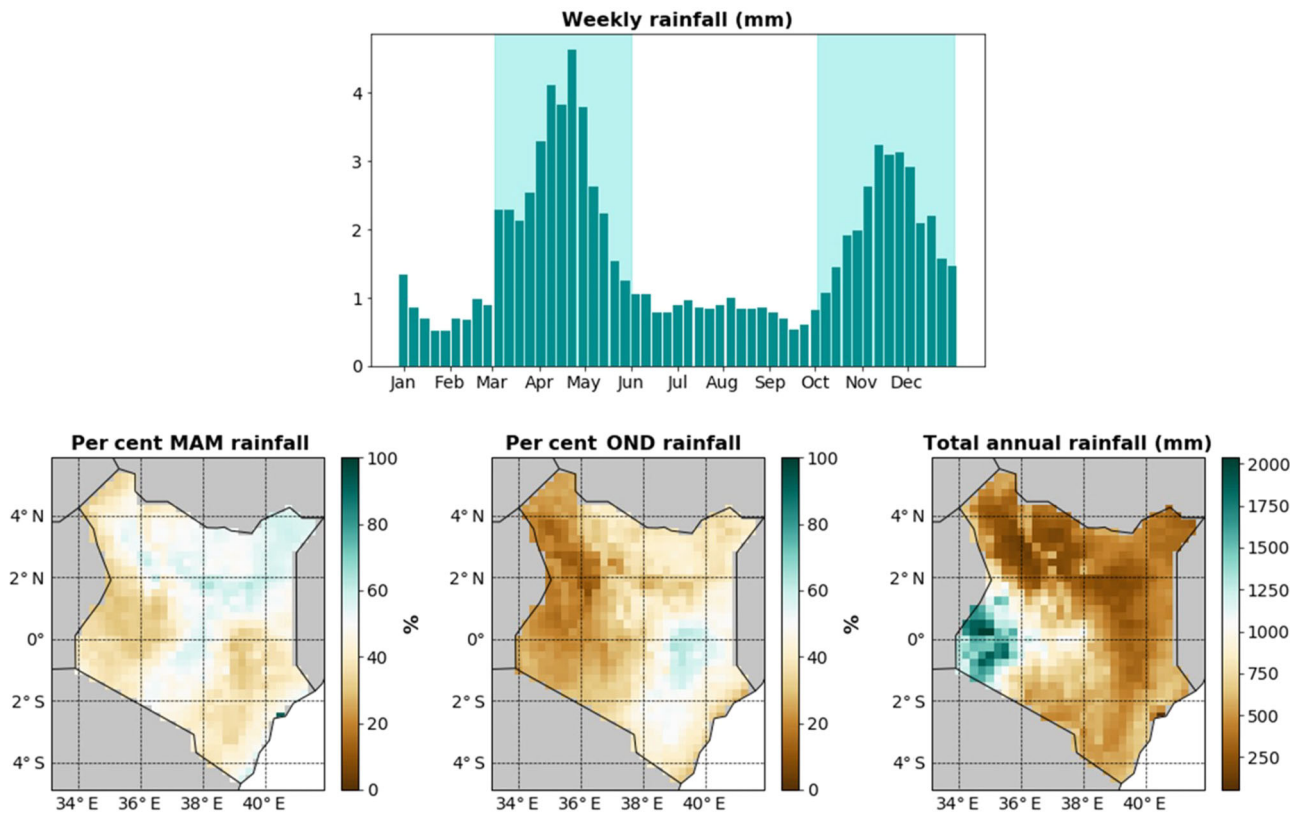
FIGURE 1 Distribution of rainfall in space and time. In Kenya, rainfall is largely restricted to two wet seasons: The March–May "long rains" and the October–December "short rains" (shaded blue areas on the time series). The climatology time series represents a national average based on the 1983–2019 historic period. Mean total annual rainfall (1983–2019) is widely < 800 mm, with the exception of western counties and the central highlands. Rainfall data from Tropical Applications of Meteorology using SATellite Data (TAMSAT), v. 3.0 (Maidment *et al.*, 2017). On the maps, grey shaded areas mask surrounding countries; and a white area indicates the Indian Ocean

semi-arid and arid regions, both seasons (March–May and October–December) contribute near equally to annual maize production (Hassan, 1996). The seasonal predictability of rainfall varies between the March–May and October–December seasons, with predictability in March–May low compared with the October–December short rains, potentially limiting the possibilities for anticipatory action in the March–May season (Young *et al.*, 2020). Although less maize is produced during the short rainy season on a national scale, several of the most vulnerable arid counties in Kenya depend on this growing season. These counties would benefit greatly from the anticipatory action enabled by skilful seasonal and monthly forecasts.

2 | METHODS AND DATA

This section begins by describing the methodology for the modelling of soil moisture and the WRSI, then explains the T-A approach to forecasting. It then describes the

crop yield and pasture availability data used to evaluate the suitability of T-A for anticipatory drought-risk management, and finally explains the analysis used to address the two points above in the Introduction.

2.1 | General methodology for modelling soil moisture

The soil moisture modelling approach adopted in the present study is based on that used in the Joint UK Land Environment Simulator (JULES), which is based on the Met Office Surface Exchange Scheme (MOSES). JULES is a land-surface model incorporating vegetative, soil, hydrological, radiative and energy balance components of the land surface. The model is driven with meteorological forcing data and outputs soil and vegetative properties. The JULES/MOSES methodology is fully described by Cox *et al.* (1999), Best *et al.* (2009, 2011), and Clark *et al.* (2011) and is summarized in Appendix S1 in the supplemental data online. In order to speed up

computation, and hence to allow the system to be implemented over large regions, several adaptations have been made to the JULES method. Unlike JULES, the model does not include full photosynthesis or radiation schemes, resulting in differences to the way that potential evapotranspiration and stomatal conductance are derived. Furthermore, in order to adapt JULES for the computation of the WRSI for a growing crop, the JULES soil moisture scheme was combined with a growing degree-day model that allows rooting depth, leaf area index and canopy height to be varied according to crop development stage (for a full description of these methods, see Appendix S1 online).

As a result of the modifications listed above, the model requires different driving data to JULES. Specifically, rather than long and short wave radiative fluxes, skin temperature is prescribed. The meteorological driving data required to run the model at the daily scale are thus: 2 m daily mean air temperature, 2 m maximum air temperature, 2 m minimum air temperature, skin temperature, surface pressure, 10 m wind speed, 2 m surface humidity and precipitation. The model is run at an hourly time step using the JULES methods for disaggregating the daily driving data to the hourly scale. In the present study, all variables are extracted from the National Centers for Environmental Predictions (NCEP) reanalysis (Kalnay et al., 1996), other than precipitation, for which TAMSAT v. 3.0 daily data are used (Maidment et al., 2017). The NCEP reanalysis data were chosen because, unlike other reanalyses, the data are freely available with a latency of only 2–3 days. All driving data are regridded to a common 0.25° scale, representing a balance between meaningful subnational variation and computational expense. Calculations are performed for land points only.

The model has the capability to represent variable soil texture, but in the present study, uniform soil textures were prescribed, primarily because we found using variable soil texture maps introduced spurious spatial step changes in soil moisture which would cause confusion for users. In future we plan to explore the latest soil texture maps including Africa Soil Information Service products (Hengl et al., 2015). Key variability in soil textures was nonetheless incorporated. Specifically, for pasture availability runs, the soil texture was set to silt loam (sand 20%; silt 65%; clay 15%) and for the crop runs, the soil texture was set to sandy loam (sand 65%; silt 25%; clay 10%). We altered the soil texture between pasture and crop runs because it is reported that farmers tend to plant maize in faster draining more sandy soils (where they are available), even though the dominant soil texture in our regions is more fine-grained.

In the model, vegetation properties are prescribed in a similar way to JULES, except that there is no capability to tile vegetation or to vary plant function types over a grid. For the purposes of the study, natural vegetation is assumed to be a uniform, shallow rooting C3 grass. Rooting depth, leaf area index and canopy height are held constant throughout the season. The treatment of crops is described below.

2.2 | Modelling soil moisture in regions of crop cultivation: Deriving the WRSI

The soil moisture model used in the present study was adapted for crops by allowing the leaf area index (LAI), plant height (h) and rooting depth (rd) to vary in both space and time. The variables LAI, h and rd are based on a growing degree-day (GDD) model, for which the plant development stage and hence the LAI, h and rd depend on prescribed crop-specific GDD. Within a region, these stages will be reached on different dates, depending on the temperature (for a further explanation, see Miller et al., 2001). For the study, planting date was assumed to be uniform over the whole region, and the GDD-based development stages were based on climatological temperatures, rather than being allowed to vary interannually.

The WRSI is defined as the ratio of cumulative actual crop evapotranspiration to the cumulative potential evapotranspiration, calculated from planting to harvest. The full method for calculating the WRSI, and its relationship to soil moisture, is described in Appendix S1 in the supplemental data online and in Asfaw (2019) (based on McNally et al., 2015). In the present study, we compare the WRSI with the observed crop yield, testing the assumption that in Africa (where crops are rain fed), the primary limit on yield is the availability of water.

Here, when referring to the WRSI for the March–May (October–December) season, we consider the WRSI for the full growing period of maize planted in March (October). A variable harvesting date is allowed, based on the climatological GDD model described above.

2.3 | Forecasting of seasonal mean soil moisture and the WRSI

In the present study, the T-A forecasting method described by Asfaw et al. (2018) is used to produce spatially variable probabilistic forecasts of soil moisture. This method is summarized as follows.

The T-A system aggregates meteorological metrics (such as precipitation) over user-defined periods, which can include both the past and future. Land-surface

metrics, such as soil moisture, and agricultural metrics, such as crop yield, can be derived by driving impact/land-surface models with the aggregated meteorological time series. The conceptual framework of T-A is shown in Figure 2. Time series of meteorological variables are generated by splicing together historical data (observations or reanalysis) with an ensemble of possible weather futures. The future weather ensemble is the weather that has occurred at the locality in question in the past, where each ensemble member represents the weather during a historical year.

In effect, T-A is an ensemble forecasting system, with ensemble members based on possible weather futures, derived from the climatology. Predictions of seasonal metrics are derived by statistically analysing the ensemble (Figure 3). T-A can thus be used to monitor and predict any metric that can be derived from environmental time-series data. It should be noted that T-A can be run without recourse to any proprietary data.

In its default state, T-A treats all possible weather futures as equally likely. Meteorological forecast information can be integrated by weighting the ensemble, using information from forecasts to judge the likelihood of each ensemble member. Therefore, if it is predicted that there is a 20% chance of upper tercile March–May rainfall, ensemble members for which March–May rainfall is in the upper tercile are downweighted accordingly. This method of weighting implicitly accounts for the inevitable mismatch between the forecast variable (e.g. March–May precipitation) and the metric of risk (e.g. crop yield). If the metric and forecast variable are not closely associated,
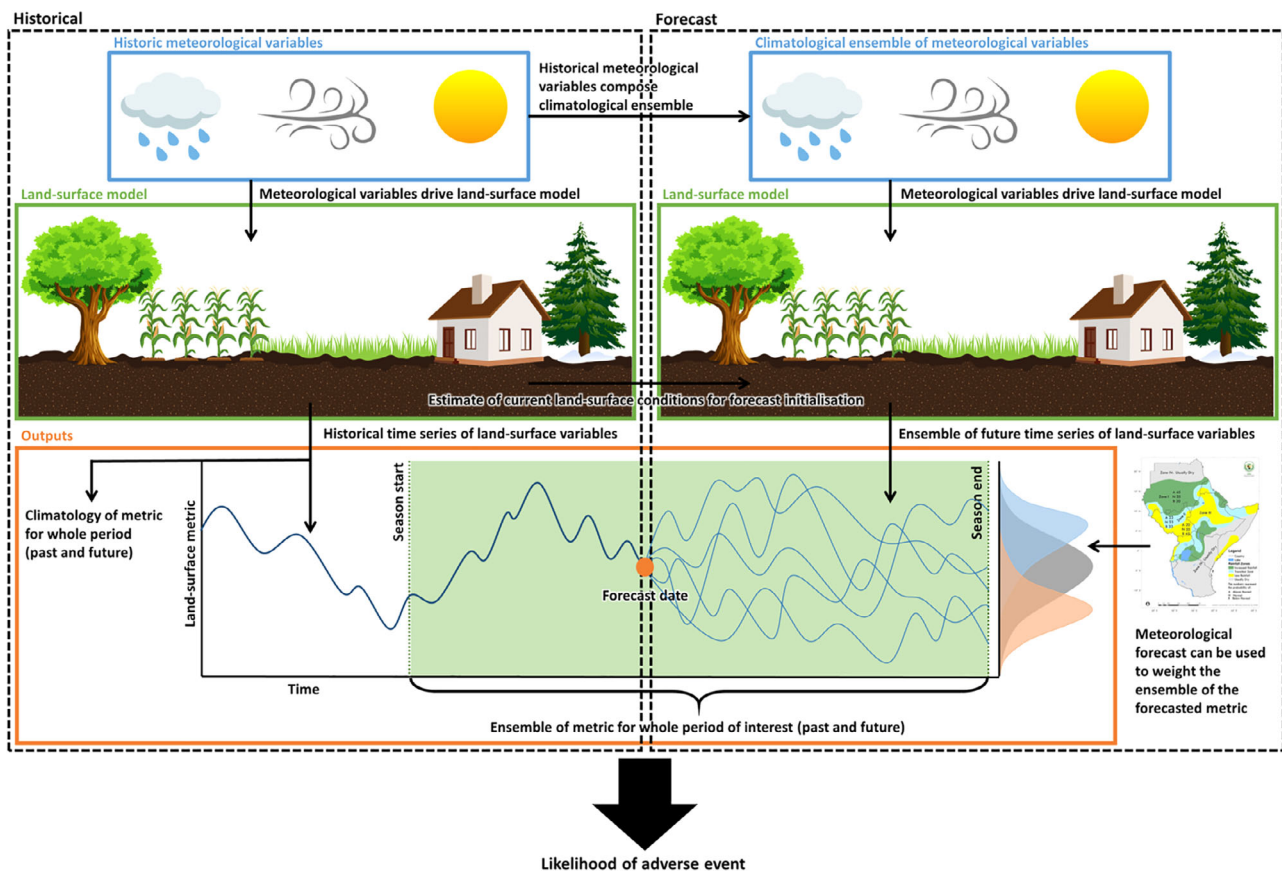

FIGURE 2 The Tropical Applications of Meteorology using SATellite data—AgriculturaL Early waRning sysTem (TAMSAT-ALERT) framework. Historical: Historical meteorological variables are used to drive the land-surface model to produce a historical time series of land-surface variables. The historical time series of land-surface metrics provides a climatology of land-surface metrics for the period of interest. Forecast: Historical meteorological variables are used to construct the climatological ensemble of meteorological variables. The initial conditions of the land-surface model are estimated from the historical run. Using each of the climatological ensembles of meteorological variables, the land-surface model is driven forward in time to produce an ensemble time series of future land-surface conditions. Combining the historical time series and ensemble of future land-surface variables, an ensemble of the land-surface metric of interest can be derived for the whole period (incorporating the historic or observed period and the forecast period). The ensemble can be weighted based on a related meteorological forecast. Considering both the historical and ensemble time series, the likelihood of an adverse event can be estimated

FIGURE 3 Example of the production of a probabilistic assessment of soil moisture using the Tropical Applications of Meteorology using SATellite data—AgriculturaL Early waRning sysTem (TAMSAT-ALERT). In this example, the forecast is issued on May 1, 2013, assessing soil moisture for the 2013 March–May season in Kitale, Kenya. (a) Time series of soil moisture. The period of interest is delineated by the vertical lines; the historical estimates until the forecast date are shown by the black bold line; the shaded polygon encloses the 10th–90th percentiles of the forecast soil moisture; and the other lines are the climatological percentiles of soil moisture for the region and day of the year under consideration. (b) Probability that the seasonal soil moisture will fall into each of the quintile categories from very low to very high
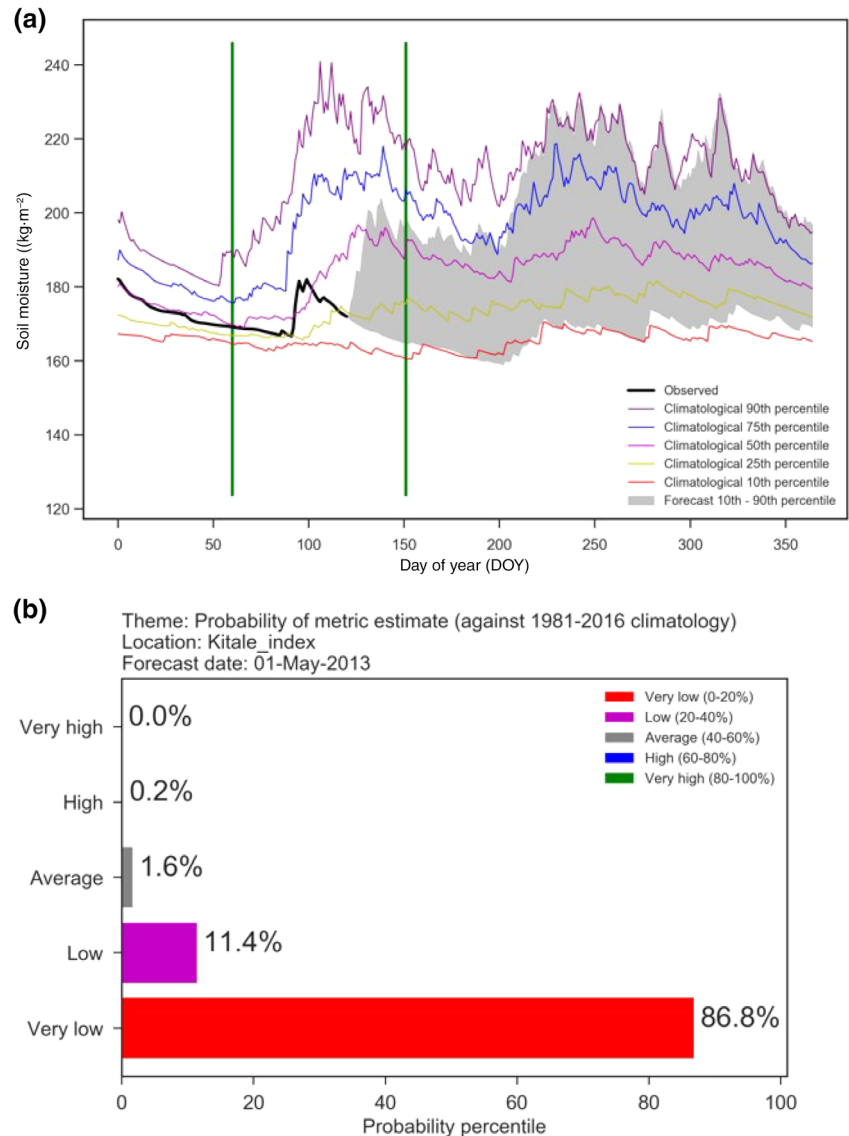
the effect of the weighting is just to randomly weight some ensemble members more strongly than others. The effect on the risk assessment will be minimal.

Here we assess the impact of weighting the T-A ensemble using meteorological reforecasts of seasonal (three month), two-monthly (two month) and monthly (one month) total precipitation, expressed as tercile probabilities, from the European Centre for Medium Range Weather Forecasts' (ECMWF) seasonal forecasting system (SEAS5) (Johnson *et al.*, 2019). The SEAS5 hindcasts (reforecasts) were provided by the Copernicus Climate Change Service (C3S) Climate Data Store (Raoult *et al.*, 2017) and have 25 ensemble members, a horizontal resolution of 1° and cover the 24 year period of 1993–2016. We use hindcasts initialized on the first day of the season/month of interest (zero month lead). Grid-point tercile probabilities are computed from the SEAS5 ensemble of total

precipitation, using tercile boundaries derived from the hindcast climatology with the year of interest removed. T-A is then weighted using the areal mean tercile probabilities derived from all grid-points over Kenya. T-A is weighted to SEAS5 tercile probabilities corresponding to three month total rainfall during the first month of a three month season, two month total rainfall during month 2, and one month total rainfall during month 3.

In essence, T-A provides a quantitative answer to the question: Given the rainfall forecast, the climatology, the stage of the growing season, the state of the land surface, the weather so far in the season of interest and the meteorological forecast, what is the likelihood of some adverse event?

T-A is a general framework that can incorporate any impact or land-surface model, which is driven with meteorological data. In this application, T-A will be run using

the WRSI/soil moisture modelling approach described above.

2.4 | Validation data: Pasture and yield indices

2.4.1 | Pasture availability

Historic measures of pasture availability were obtained from the Global Inventory Monitoring and Modelling System (GIMMS) project's normalized difference vegetation index (NDVI). The NDVI correlates closely with ground-based measures of vegetation dynamics including biomass, net primary productivity and leaf area index (Tucker *et al.*, 1985; Reed *et al.*, 1994; Pettorelli *et al.*, 2005).

Specifically, we used the NDVI3g.v1 data set, which extends from July 1981 to December 2015 and provides the bimonthly NDVI measures at an 8 km resolution, globally (Pinzon and Tucker, 2014).

We spatially and temporally aggregated NDVI3g.v1 data to obtain the mean seasonal NDVI at 0.25° resolution (to match the resolution of soil moisture data). We excluded NDVI data outside of key pastoral zones. Pastoral zones were determined using livelihood zone definitions provided by FEWSNET (2011). The mean seasonal NDVI from pastoral zones was subsequently used to calculate the vegetation condition index (VCI) using the methods of Yang *et al.* (2011). The VCI compares the NDVI recorded in a given year to that observed over the same period in other years. It is expressed as a percentage, with 0% and 100% representing the lowest and highest observations of the NDVI, respectively. Here, the VCI was calculated for the season of interest with a 15 day lag in season start and end in order to account for the known lag between soil moisture and vegetation growth. The VCI has been shown to be a good indicator of drought (Liu and Kogan, 1996) and is already used by Kenya's National Drought Management Authority (2018) as an indicator of vegetation condition and pasture availability.

2.4.2 | Maize production

Data on maize production were obtained from the Food and Agriculture Organization's (FAO) statistics database (FAO, 2020a). The database contains annual production data (expressed as area harvested, production quantity and yield) for primary crops in all 194 member nations from 1961 to 2018. Data are largely provided by governments in response to the FAO's annual production questionnaires and through national publications. Where these data are unavailable, data may be obtained from unofficial sources or imputed.

For national-level comparison, we used maize total production quantity data (equal to yield *per* hectare multiplied by area harvested) to account for both the amount of land under maize production and the yield obtained from that land (both expected to increase in wetter years). In the 1983–2018 study period, all production data for Kenya were collated from official sources. However, the FAO notes that the quality of these data cannot be guaranteed. Data are collected through annual production questionnaires, national publications and official websites, but the original source of data and the methodology used to collect them are not currently documented, and so reliability may vary (FAO, 2020b). This should be kept in mind when interpreting the results.

Given the spatial variability of drought conditions, we also considered maize production at the county level. We obtained maize yield data for 45 counties of Kenya from FEWSNET covering the period from 1981 to 2014. The data provide an annual yield for the calendar year. At the county level, we considered yield *per* hectare, rather than total production (as for national-level comparisons), to allow for a comparison across counties of different areas. As with the national-level FAO production data, county-level FEWSNET yield information does not provide an indication of reliability, and it is possible that methods of data collection vary between counties and over time.

2.5 | Analysis

2.5.1 | Historic validation of T-A soil moisture and WRSI

The mean seasonal soil moisture estimates for Kenya's March–May and October–December seasons were compared with the mean seasonal VCI using Pearson's correlation co-efficient (r; $p < 0.05$ is deemed significant). The correlation was assessed for Kenya as a whole and on a gridded basis to understand how this relationship varies spatially. It should be noted that we are validating one proxy (T-A soil moisture) against another (VCI). We are therefore assuming that the VCI provides a "true" picture of pasture availability. Whilst this is not an ideal assumption, given the lack of empirical data, we felt that this was a suitable course of action.

The mean seasonal WRSI estimates were similarly compared with annual maize yield at a national level. In addition, the correlation between annual county maize yield and the gridded WRSI was also computed to understand the spatial variations in their relationship.

However, for both the country- and county-level maize yield data, annual yield totals were not divided between Kenya's two rainy seasons. The March–May long rains represent the major growing season across Kenya, and hence we assessed the relationship between national-level maize yield and the WRSI only for the March–May season. However, maize and some other crops are also grown in the October–December short rains, mostly in northern and eastern regions. Therefore, we assessed the county-level relationship between the WRSI and maize yield for both seasons.

In order to clarify the value of soil moisture and the WRSI in predicting the VCI and maize yield, the seasonal VCI and annual maize yield totals were also compared to confirm that the VCI does not provide a more direct means of monitoring crop production.

2.5.2 | Assessing the skill of soil moisture and WRSI forecasts

The T-A forecasting system was used to generate hindcasts of seasonal mean soil moisture and the WRSI for each year in the climatological period. We chose to use a relatively short 15 year climatological period (2003–2017) because of the interdecadal variability in the region.

Hindcasts were generated every week from the beginning to the end of the season to assess the influence of lead time on forecast skill. Here, we use lead time to refer to the number of days before the end of the season rainy season (May 31 and December 31 for the March–May and October–December seasons, respectively). The resulting soil moisture ensemble forecasts were compared with historic simulations of mean seasonal soil moisture and the VCI, and the WRSI ensemble forecasts were compared with historic simulations of the WRSI and maize yield using Pearson's correlation co-efficient (r).

Ensemble forecasts were also used to calculate the probability of seasonal mean soil moisture and the WRSI being < 20th percentile. Years in which soil moisture or the WRSI falls to < 20th percentile represent extreme drought years or a one-in-five year drought event. This return period represents a trade-off between acting on events that cause food insecurity and balancing financial restraints. Comparison of the forecast probability with observed classifications was used to calculate the true-positive and false-positive rates, indicating the ratio of hits, misses, false-alarms and correct rejections (Coughlan De Perez et al., 2015). The true-positive and false-positive rates were subsequently used to generate the receiver operating characteristic area under the curve

(ROC-AUC) scores (Mason and Graham, 2002). The ROC-AUC scores are generated by plotting the true-positive rate against the false-positive rate over a range of probability thresholds and calculating the area under the resulting curve. The scores are used to determine how well a probabilistic forecast can delineate a particular event, in this case, for example, soil moisture < 20th percentile and soil moisture > 20th percentile. The ROC-AUC scores range from 0 to 1, with values representing the following:

- ROC-AUC < 0.5: the forecast can delineate events, but events are mislabelled.
- ROC-AUC = 0.5: the forecast has no delineation skill, or a random chance of correctly delineating events.
- ROC-AUC > 0.5 to < 1: the forecast has a better than random chance of correctly delineating events.
- ROC-AUC = 1: the forecast can perfectly delineate events.

Here we deemed any ROC-AUC > 0.8 as representing a skilful forecast. This threshold in determining a sufficiently skilful forecast is demonstrative in this case, but can be altered to account for the varying implications of incorrectly delineating an event. For instance, actions that have a higher cost of acting in vain should only be triggered by highly skilful forecasts (high ROC-AUC scores), whilst low-regret actions may be based on forecasts with lower ROC-AUC scores. This concept is addressed in more detail in Section 4.

We generated ROC-AUC scores from hindcasts at a range of lead-times throughout the season to assess the skill of T-A forecasts in identifying years in which soil moisture, the WRSI, the VCI and yield were < 20th percentile. In order to demonstrate the added value of the meteorological forecasts, we compared the probabilistic soil moisture, VCI and WRSI forecasts that incorporate meteorological forecasts with forecasts based purely on observations.

3 | RESULTS

3.1 | Historic validation of T-A soil moisture and WRSI

3.1.1 | Soil moisture: VCI

For both rainy seasons, soil moisture correlates strongly with the VCI at national and seasonal scales (Figure 4). This relationship is stronger in Kenya's October–December season (Figure 4b; $r = 0.89$) than for March–
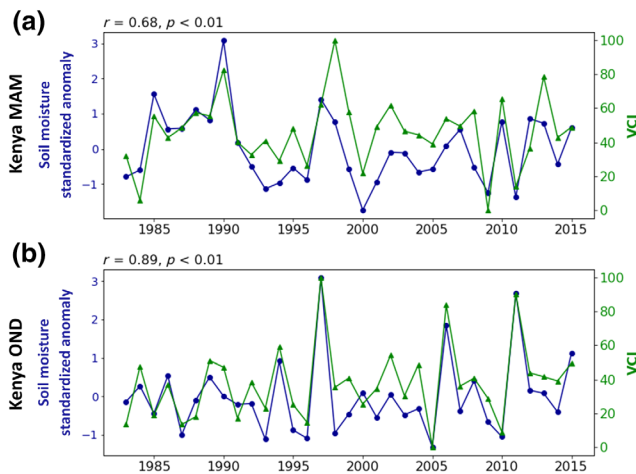
FIGURE 4 Interannual variation of national-level soil moisture (circles) estimates compared with the vegetation condition index (VCI) (triangles). Both metrics represent mean seasonal values. Soil moisture anomalies are standardized. Pearson's correlation co-efficients (r) are presented above each plot. For both seasons, soil moisture and the VCI are significantly (p < 0.05) and positively correlated

May (Figure 4a; $r = 0.68$), but both show good agreement.

Also important to anticipatory drought-management applications is that soil moisture correctly identifies an anomalously low seasonal VCI given that the VCI is a proxy for pasture availability. Indeed, in both seasons, the lowest VCIs are correctly accompanied by low soil moistures. This suggests there are no instances in which T-A soil moisture "missed" the anomalously low VCI conditions, at least on the national scale.

However, there are a few cases where soil moisture anomalies are low compared with the VCI, suggesting a "false-alarm" would have been issued. This is clear during the March–May seasons of 1993, 1999, 2000 and 2001, and in the 1998 October–December season.

Spatially, soil moisture and the VCI climatologies follow largely similar patterns in both rainy seasons (Figure 5) and are broadly similar to rainfall climatologies presented in Figure 1. Soil moisture is generally highest in western counties surrounding Lake Victoria. These wetter soil conditions extend further east during the March–May long rains when compared with the October–December short rains (Figure 5a, d). The VCI shows a similar spatial pattern, but is also high in Kenya's central highlands and along the Indian Ocean coast.

The correlation between seasonal soil moisture and the VCI varies across Kenya and is generally more strongly positive in areas where the VCI climatology is low (Figure 5c, f). For instance, weaker correlations occur

in Kenya's western counties, and correlations along the coastal region, where the VCI is climatologically high, are insignificant ($p > 0.05$). In addition, the correlation between mean seasonal soil moisture and the VCI is generally stronger in the October–December short rains when compared with the March–May long rains.

3.1.2 | VCI: Yield

We compared the mean seasonal VCI with national-level maize yield to determine whether the VCI, already commonly used by drought-management stakeholders, provided a better proxy of yield than the WRSI. Whilst the VCI does capture some of the maize failure years in the time series for Kenya, the comparison of the seasonal VCI with maize yield was statistically insignificant (Figure 6).

3.1.3 | WRSI: Yield

Although not as strongly positive as the correlation between soil moisture and the VCI, the correlation between the national-level WRSI and maize yield is statistically significant ($p < 0.05$), and fair given the myriad of factors beyond the WRSI that influence maize yield (Figure 7; $r = 0.43$). Moreover, the correlation between the WRSI and yield is stronger that that between the VCI and yield (Figure 6) and between rainfall (TAMSAT v. 3.0) and yield ($r = 0.38$, $p < 0.05$) (see Figure S1 in the supplemental data online).

However, when considering the ability of the WRSI to identify the worst maize yield years, the WRSI "missed" low yield in the 1984, 1997, 1998 and 2008 March–May seasons. In terms of "false-alarms", anomalously low WRSIs were not met with low yield in Kenya's 1994 and 2017 March–May seasons.

At the county level, the correlation between interannual variations in the WRSI and maize yield varies across Kenya and between seasons. Figure 8a, c shows the gridded correlation between the seasonal mean WRSI and annual county yield. For both the March–May and October–December seasons, correlations are largely positive, but in some cases are negative. Looking in more detail, Figure 8b, d shows interannual variation in the WRSI, county maize yield and the NDVI for Isiolo county. This demonstrates the disconnect between biophysical metrics (WRSI and NDVI) and county-level maize yield. In this example, the variability of yield seems to reduce in later parts of the time series, possibly relating to changing management practices not captured by the WRSI. Furthermore, interannual variation in yield is
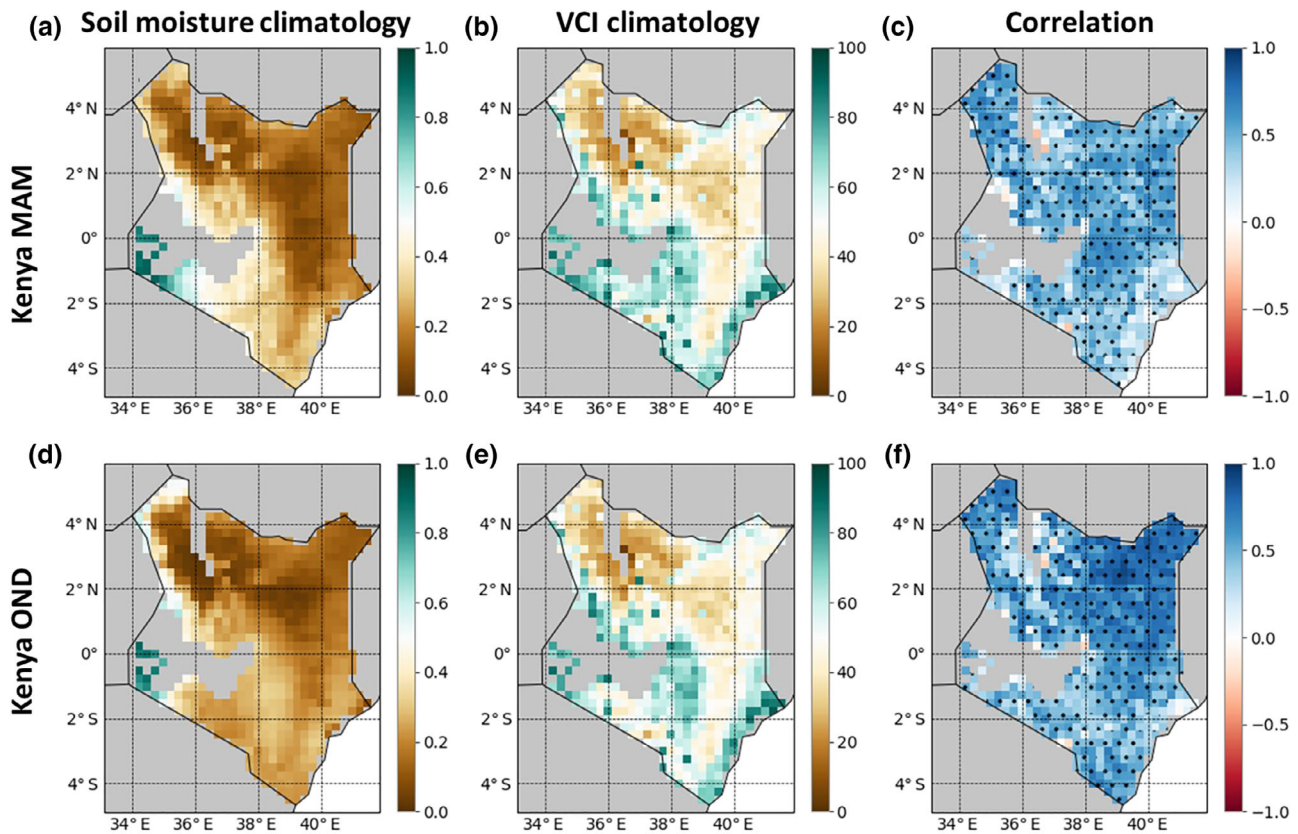
FIGURE 5 Comparison of soil moisture (β) and the vegetation condition index (VCI) (%) climatologies across Kenya for each wet season. Pearson's correlation co-efficient (r) is presented in the third column and indicates the relationship between interannual variation in seasonal mean soil moisture and the VCI. Darker blue colours show a strong positive correlation; and red shows a negative correlation. Grey areas are masked to exclude surrounding countries and regions where pastoralism is not a major livelihood. White areas indicate the Indian Ocean. Stippling indicates statistical significance ($p < 0.05$)
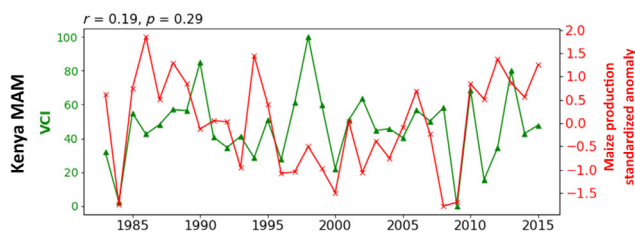

FIGURE 6 Interannual comparison of the seasonal mean vegetation condition index (VCI) (triangles) compared with annual maize yield (crosses). Yield anomalies have been standardized. Pearson's correlation co-efficients (r) are presented above the plot. At the national level, the relationship between the VCI and yield is not statistically significant ($p > 0.05$)
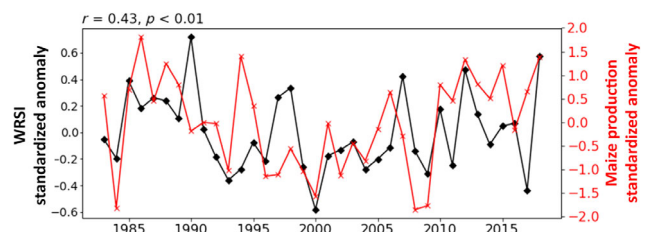

FIGURE 7 Interannual comparison of seasonal mean water requirement satisfaction index (WRSI) (diamonds) and annual maize yield (crosses). Yield anomalies are standardized. Pearson's correlation co-efficients are presented above the plot. At the national level, there is a statistically significant ($p < 0.05$) relationship between the WRSI and yield

inconsistent across counties, with poor correlations between counties (see Figure S2 in the supplemental data online). There are, moreover, stark differences in the WRSI/county yield correlation from one county to another. For example, in Kenya March–May (Figure 8a), Makueni county is negatively correlated, whilst neighbouring Kitui county is consistently positively correlated.

These inconsistencies point to inhomogeneities and quality issues with the county yield data. As mentioned in Section 2.4, full details on the data-collection methodology, both over time and across counties, are not currently available, making it difficult to assess the reliability of maize yield data fully.
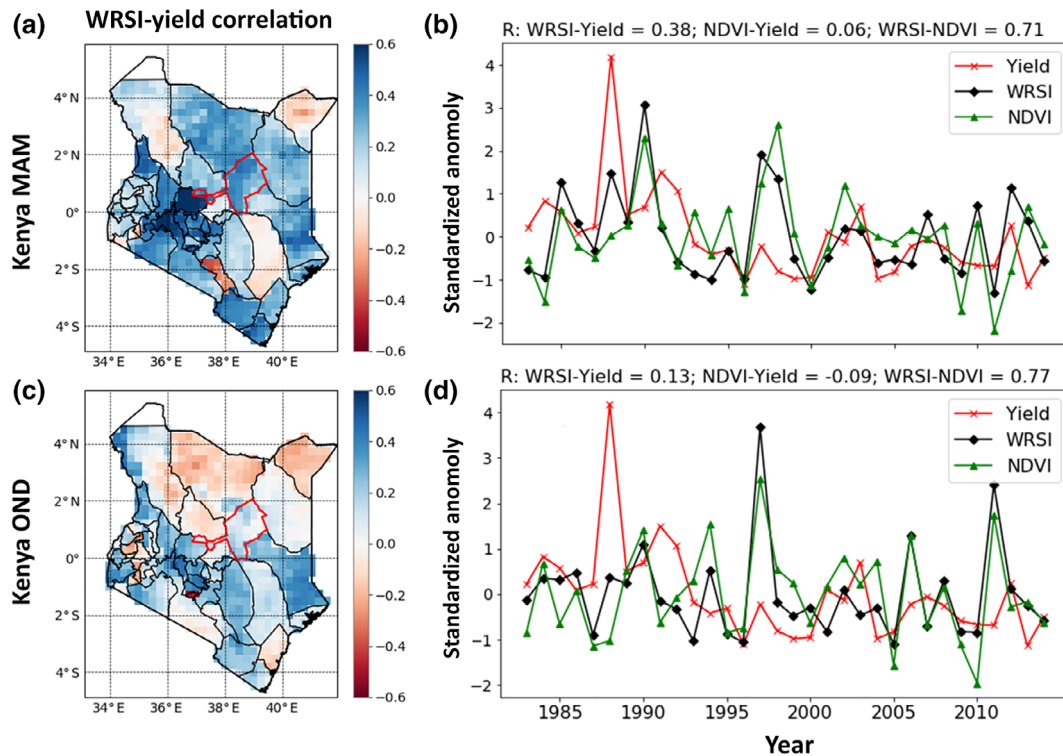
FIGURE 8 Interannual correlations (Pearson's *r*) between county maize yield and the seasonal mean water requirement satisfaction index (WRSI) vary across Kenya and between the March–May and October–December seasons (a, c). Isiolo county is highlighted in red. The time series shows interannual variation in county maize yield (crosses), the mean seasonal WRSI (diamonds) and normalized difference vegetation index (NDVI) (triangles) for Isiolo county as an example (b, d)

Kenya has two rainy seasons, which complicates the comparison of the seasonal mean WRSI with annual maize yield. The annual yields provide no information on the planting and harvest dates. It is likely that in some counties maize is planted in October; in others, maize is planted in March; and in some, maize is planted in both growing seasons. The contribution of each season to annual maize yields is not available at the national or county level. Figure 8 shows that for most counties the WRSI based on a March planting date correlates more strongly with yield. However, in other counties, the October seasonal WRSI has a higher correlation with yield.

Considering the spatial correlation between the WRSI and county-level maize yield, we see that counties with a climatologically higher WRSI also have climatologically higher maize yield (March–May: $r = 0.78$, October–December: $r = 0.76$, $p < 0.05$) (Figure 9). In individual years, the spatial correlation between the county WRSI and maize yield can be high, although it also exhibits some interannual variability (March–May: mean $0.67 \pm$ SD 0.11, October–December: mean $0.61 \pm$ SD 0.12) (Figure 9d). This suggests that in some years it is possible to identify counties particularly at risk of low yield.

3.2 | Forecast skill

The analysis of hindcasts to identify the lead-time at which T-A soil moisture and WRSI forecasts can reliably and skilfully predict observed values revealed that, for both seasons, soil moisture, the WRSI, the VCI and maize yield can be forecast with some accuracy ahead of the end of the season.

3.2.1 | Influence of lead time on skill

Soil moisture
The soil moisture ensemble forecast mean correlates strongly ($r > 0.8$) with observed March–May values by the end of April (up to 35 days before end of season) (Figure 10a) and can skilfully (ROC-AUC > 0.8) identify one in five year drought events (< 20th percentile) by early April (up to 56 days before the end of the season) (Figure 10b).

Whilst early season correlation and skill is lower in the October–December than the March–May season (Figure 10), the correlation between the soil moisture forecast and observed October–December values increases rapidly through October and correlates strongly
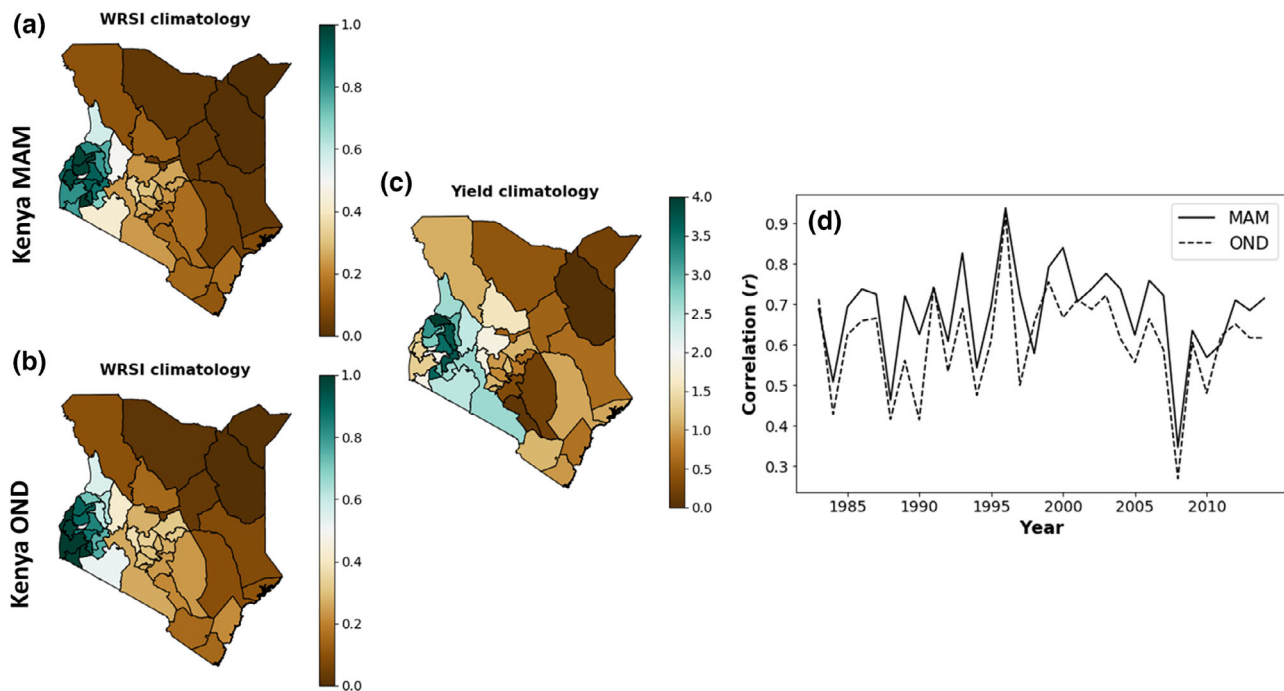
FIGURE 9 County seasonal water requirement satisfaction index (WRSI) climatology (March–May: a; October–December: b) and annual yield (c) long-term mean compared spatially. Overall, there is a strong positive relationship between the climatological WRSI and the long-term mean yield of a county, so that counties with a higher climatological WRSI have a higher mean yield. This holds for both seasons. However, the spatial correlation between the WRSI and yield varies interannually (d)

by early November (56 day lead time). Moreover, the ability for the soil moisture forecast to identify drought years (< 20th percentile) is skilful by the end of October (63 day lead time).

VCI

The soil moisture ensemble forecast mean also correlates well with the observed seasonal VCI in both March–May and October–December seasons, with the *r*-value nearing 0.8 by mid-April (Figure 10a) and surpassing 0.8 by late November (Figure 10c), respectively. The ensemble forecast also shows consistent and reasonable skill throughout both seasons in identifying the years where the seasonal VCI is < 20th percentile (Figure 10b, d), although the forecasts are generally more skilful in the October–December season.

WRSI

We assessed the WRSI forecasts for the March–May season only, since, at the national level, March–May contributes more substantially to annual maize yield than October–December. From the very beginning of the March–May season, the WRSI forecast correlates strongly with observed values (Figure 10a), with a slight decline mid-season, possibly related to shifts in meteorological regimes as the season progresses. In addition, the WRSI

forecasts skilfully identify years with a seasonal WRSI < 20th percentile just three weeks into the March–May season (Figure 10b).

Yield

The WRSI ensemble forecast mean does not correlate well with maize yield early in the March–May season, but steadily increases throughout (Figure 10a). The ability of the WRSI ensemble forecast to identify years with maize yield < 20th percentile is, however, better and can be skilfully predicted by early May (21 days before the end of the season) (Figure 10b).

3.2.2 | Incorporating meteorological forecasts

In all cases, when seasonal rainfall tercile forecasts from the SEAS5 are incorporated into the soil moisture and WRSI forecasts, both correlations between forecasts and observed values, and the skill of the forecast in its ability to identify drought years, is improved (Figure 10, dashed lines). For both the March–May and October–December seasons, the greatest improvements in the soil moisture and WRSI forecast skill are seen in the first half of the season. Improvements are also much more significant in
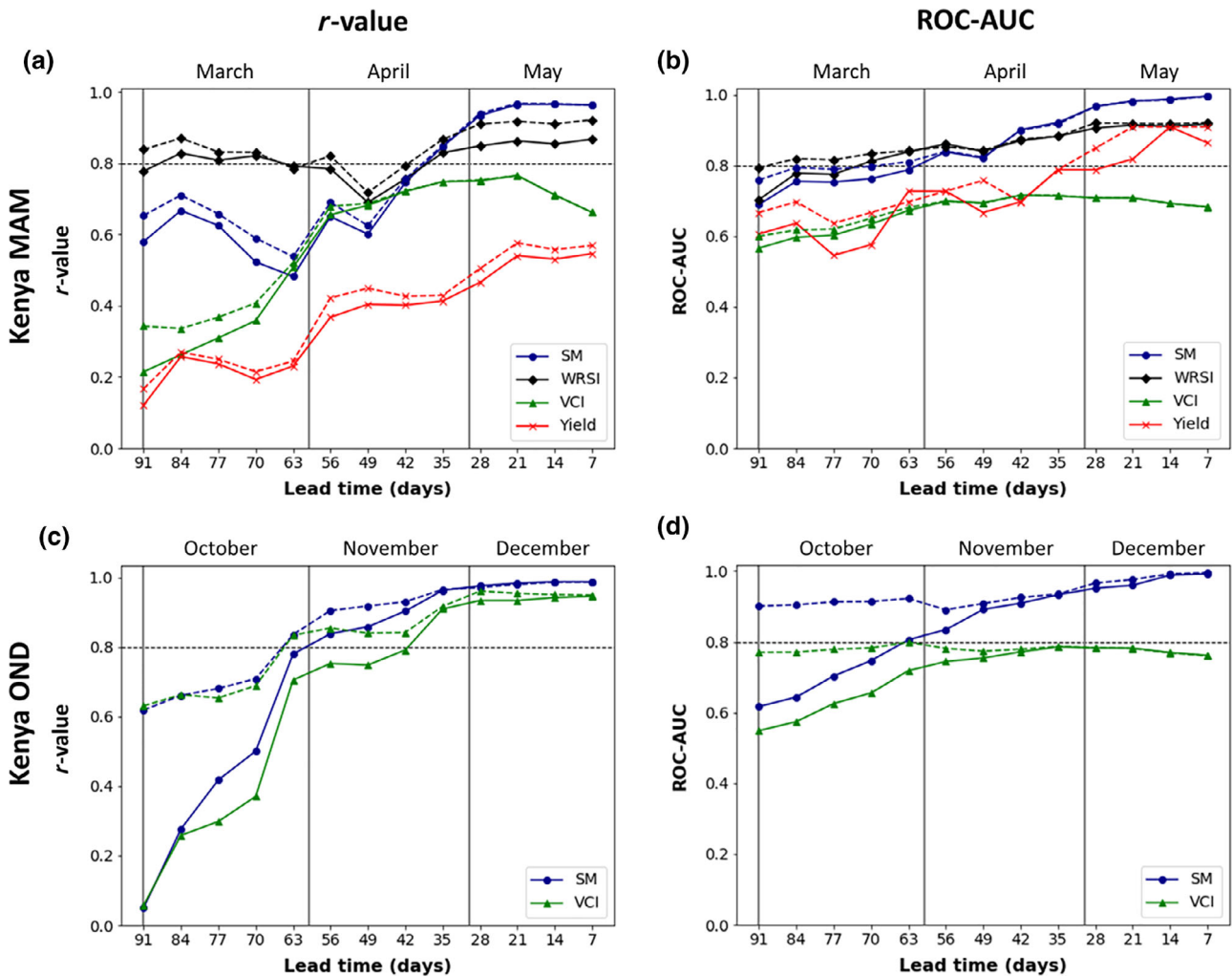
FIGURE 10 Skill of Tropical Applications of Meteorology using SATellite Data—AgriculturaL Early waRning sysTem (TAMSAT-ALERT) soil moisture forecasts as the season progresses. The first column shows the correlation (*r*) between mean seasonal soil moisture (circles), water requirement satisfaction index (WRSI) (diamonds), vegetation condition index (VCI) (triangles) and yield (crosses) against the forecast soil moisture or the WRSI ensemble mean. The second column shows the receiver operating characteristic area under the curve (ROC-AUC) scores of the ensemble mean for identifying the < 20th percentile seasonal soil moisture, WRSI, VCI and yield, at a range of lead times. Dashed lines show the skill of the respective ensemble forecasts when weighted with the meteorological tercile forecast. The beginning of each month is indicated by vertical lines. The dashed horizontal lines indicate $r = 0.8$ and ROC-AUC $= 0.8$, here used to represent "high" correlations and skill. This is for demonstration purposes only, and in designing triggers for anticipatory drought-risk management, could be adjusted to account for the varying costs of acting in vain associated with different actions (for a further explanations, see Section 4. Discussion)

the October–December season compared with March–May, most likely because the SEAS5 rainfall forecasts have greater predictive skill during this season (Young *et al.*, 2020).

The increasing skill of soil moisture and the WRSI forecasts is also shown in Figure 11. With a 63 day lead time (late March and October for March–May and October–December, respectively), the soil moisture and WRSI ensemble forecasts already show some signal which matches the observed soil moisture, VCI, WRSI and yields reasonably well. With a 35 day lead time (late April and November for March–May and October–

December, respectively), the signal in the ensemble forecasts further improves and the uncertainty in the forecasts narrows.

3.2.3 | Spatial variation in skill

In addition to considering variation in forecast skill at a range of lead times, we also considered how forecast skill varies spatially. Figure 12 shows ROC-AUC scores calculated at a range of lead times for each 0.25° grid cell. Again, ROC-AUC scores measure the ability of the soil
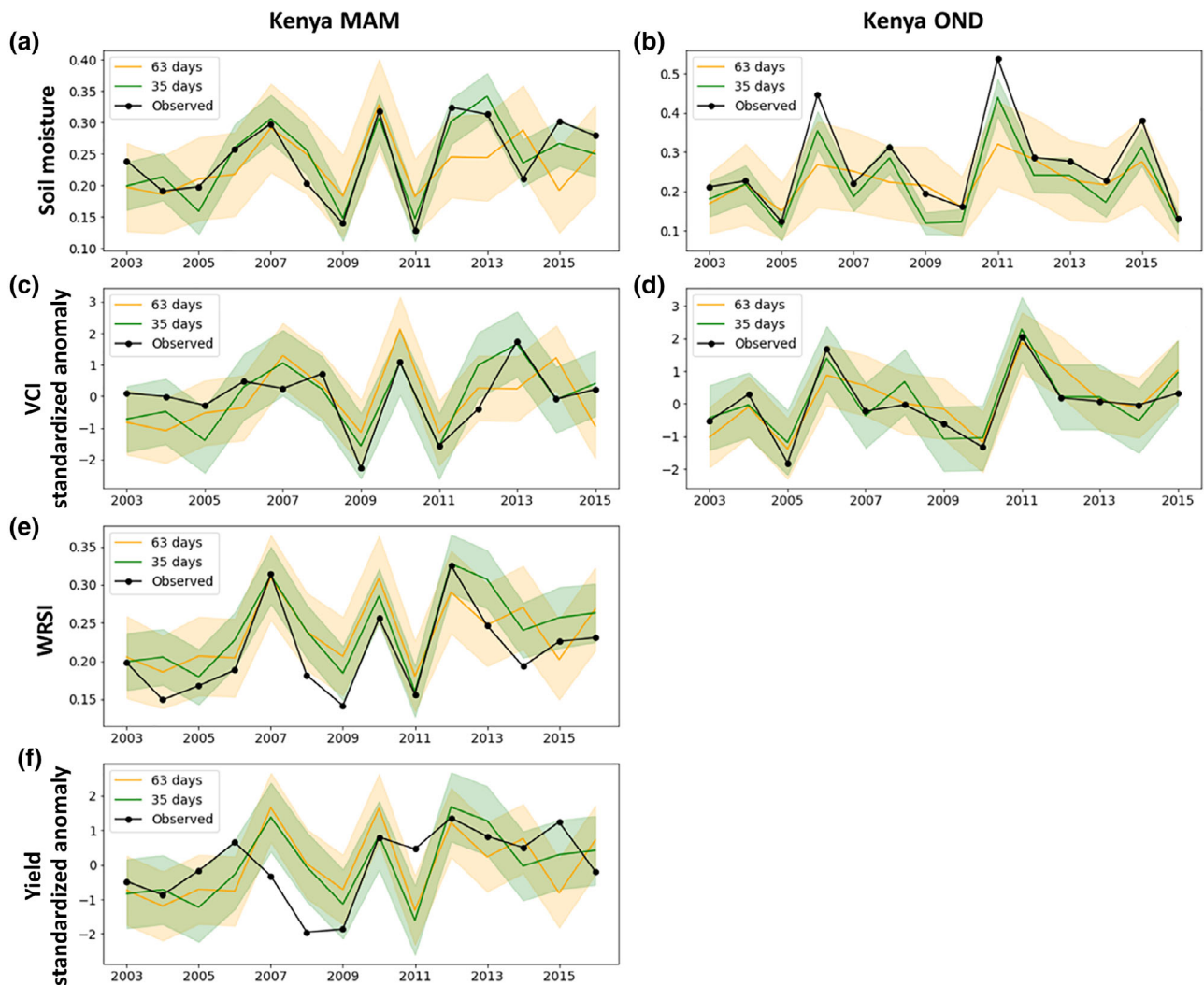
FIGURE 11 Convergence of Tropical Applications of Meteorology using SATellite data—AgriculturaL Early waRning sysTem (TAMSAT-ALERT) soil moisture and water requirement satisfaction index (WRSI) ensemble forecasts (incorporating the seasonal meteorological forecast) throughout the season. As the lead time decreases, the ensemble standard deviation narrows, and the signal in the forecasts become clearer and more closely represents estimates

moisture forecast to identify years in which seasonal soil moisture and the VCI are below their respective 20th percentiles.

Soil moisture

Th ROC-AUC scores calculated for soil moisture indicate that in both March–May and October–December seasons, the skill of soil moisture forecasts generally increases across Kenya (Figure 12) as the season progresses. However, the ROC-AUC scores do vary spatially. In March–May, the coastal and western regions show a lagged improvement in skill when compared with the rest of Kenya. For October–December, it is rather the Rift Valley region, particularly along Kenya's southern border with Tanzania, that shows lower skill. However, in agreement

with Figure 10, the ROC-AUC scores for both seasons are generally high (> 0.8) across Kenya more than a month before the end of the season.

VCI

For the VCI, spatial variation in the ROC-AUC scores is noisier than for soil moisture, but again shows a general improvement nationwide as the season progresses (Figure 12). For March–May, again the coastal region stands out as having lower skill than the rest of the country, particularly in the early and late parts of the season. In October–December, southern Kenya tends to have lower skill than elsewhere. In general, for both seasons, skill is higher in the arid and semi-arid northern counties.
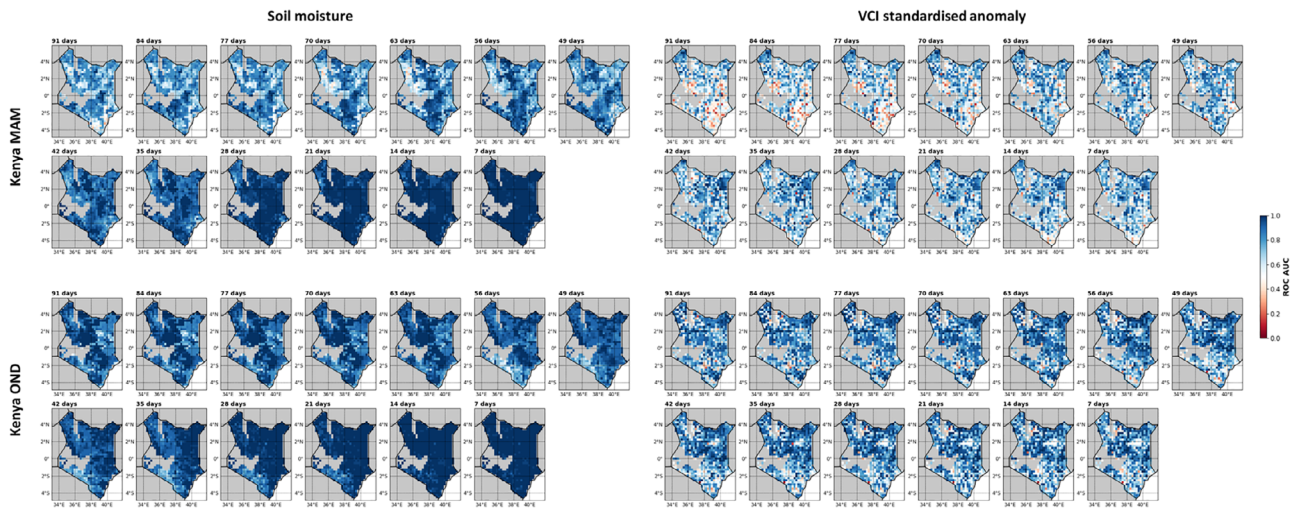
FIGURE 12 Receiver operating characteristic area under the curve (ROC-AUC) scores for identifying < 20th percentile soil moisture and vegetation condition index (VCI) using the Tropical Applications of Meteorology using SATellite data—AgriculturaL Early waRning sysTem (TAMSAT-ALERT) soil moisture ensemble forecast (incorporating the meteorological forecast) at a range of lead times for both seasons. Grey areas are masked to exclude surrounding countries and regions where pastoralism is not a major livelihood. The white area indicates the Indian Ocean

4 | DISCUSSION

4.1 | Suitability of T-A for anticipatory drought management

Analysis of T-A soil moisture and WRSI has confirmed that T-A can provide drought-impact-relevant metrics within a timeframe to allow for anticipatory actions.

4.1.1 | Relevance to drought impacts

Historic T-A estimates of soil moisture and the WRSI are positively correlated with measures of pasture availability (VCI) and maize yield in Kenya (Figures 4 and 7). Whilst the correlation between soil moisture and the VCI is stronger than the relationship between the WRSI and maize yield, this is likely because yield is influenced by several additional factors not considered here (e.g. agronomic practices, the economic and political environments). Moreover, the WRSI correlates more closely with yield than other widely used proxies including both the VCI (Figure 6) and rainfall (see Figure S1 in the supplemental data online). It is notable that the correlation between the VCI and yield is low, suggesting that whilst the VCI represents the pasture condition accurately, the additional detail of the crop calendar and deep soil processes encapsulated within the WRSI improves the prediction of crop yields. It is also likely that limitations in the yield data, namely the accumulation of seasonal yields into an annual total, constrain the

correlation with the WRSI and VCI as it cannot account for differences in cropping seasons across Kenya.

The relationship between soil moisture and the VCI is stronger in October–December compared with March–May (Figure 4). It is possible this is because October–December brings the first rainfall after 4–5 months of dry conditions (Figure 1). Pasture vegetation responds rapidly to this rainfall. In March–May, however, pasture availability is influenced not only by March–May rainfall but also by rain experienced in the preceding October–December season, and hence is less correlated with March–May soil moisture. This is consistent with the finding that the WRSI forecasts correlate positively (if weakly) with observed maize yield from the beginning of the March–May season (Figure 10), supporting that notion that antecedent conditions are more important in March–May than in October–December.

Spatially, it makes sense that where the soil moisture and VCI conditions are climatologically low, they are more closely tied to one another. Across Kenya, correlations between soil moisture and the VCI are highest in the semi-arid and arid counties in the north and east (Figure 5). In these regions, pasture availability is likely to be limited by soil moisture, and so any increase in soil moisture results in an increase in the VCI. Where correlations are lower, it is possible that factors other than soil moisture limit pasture production. Alternatively, particularly in the coastal region, insignificant correlations could be associated with the accuracy of the driving rainfall data; rainfall originating from shallower clouds, often

recorded in the coastal region, is not as well captured by TAMSAT (Dinku *et al.*, 2018).

Aside from a general agreement in the interannual variation between soil moisture and the WRSI, and pasture availability and maize yield, respectively, there were instances in which the WRSI was unable to identify poor yield correctly. Some of these "misses" can be explained. For instance, the discrepancy between the WRSI and yield in Kenya's 1998 March–May season is likely explained by the positive Indian Ocean Dipole (IOD+) and El Niño, which occurred in late 1997 (Black *et al.*, 2003; Black, 2005). The heavy rainfall associated with these events resulted in flooding and waterlogging of the soils, causing low crop yield (Amissah-Arthur *et al.*, 2002). It is also possible that political unrest in late 2007 and early 2008 caused changes to normal planting regimes (Harneit-Sievers and Peters, 2008), explaining the discrepancy in the WRSI and yield in March–May 2008.

In addition, some of the "false-alarms", in which soil moisture and the WRSI suggested poor pasture and crop production, which was not realized, can be explained. The "false-alarm" for the VCI in October–December 1998 in Kenya likely resulted because the vegetation's condition remained high following the heavy October–December 1997 rains, which limited the overexploitation and degradation of pasture usually associated with the below-average soil moisture conditions experienced throughout 1998.

Other "misses" and "false-alarms" are not so easily explained. Further investigation into soil moisture and the WRSI values at key points during the growing season (rather than seasonal means) could aid an explanation, but was beyond the scope of the study.

The occurrence of some "misses" and "false-alarms" in the historic data set is to be expected as other factors aside from soil moisture and the WRSI impact vegetation productivity. That some discrepancies are explained by the heavy rainfall event that occurred across East Africa in October–December 1997 suggests that decision-makers should be wary in using T-A soil moisture and WRSI forecasts in extremely wet periods. However, that instances of the low VCI and maize yield are mostly captured by the low soil moisture and WRSI values provides strong support for the use of T-A soil moisture and WRSI in identifying the impacts of drought.

County-level maize yield
Whilst at the national scale annual maize yield seems at least partially captured by the WRSI (Figure 7), there remains a question over the utility of national-level yield estimates in drought management. For this reason, we also investigated the ability of the WRSI to capture maize yield at the county level. The results varied, with some counties having strong correlations, and others not (Figure 8). Interannually, it is likely that factors other than meteorology influence the yield records. The low correlation between county-level yield and the NDVI suggests that the dominant reason for the poor correlations is change in production area and, possibly, the dominant growing season.

However, the WRSI was broadly able to capture spatial variation in county-level maize yield (Figure 9), with positive correlations, suggesting that counties with a low WRSI also experienced low yield. However, this relationship varies annually, with no clear indication of factors leading to stronger or weaker correlations.

These results should be interpreted conservatively since data-collection methodologies were unavailable and it was therefore impossible to assess the reliability of county-level yield estimates across counties and over time.

4.1.2 | Lead time to allow for action

Alongside the clear relevance of T-A soil moisture and WRSI for identifying the impacts of drought, T-A metrics can also be forecast with significant skill ahead of the end of both seasons, suggesting that within-season forecasts can support preparatory actions. This mirrors the results of existing drought-impact forecasting systems that demonstrate notable post-planting skill (Hansen *et al.*, 2004; Manatsa *et al.*, 2011; Shukla *et al.*, 2014).

The correlations between the soil moisture ensemble forecast and historic simulations of soil moisture and the VCI, and the WRSI ensemble forecast with the observed WRSI and maize yield, increase throughout both seasons. At the beginning of the season, correlations between the forecasts and estimates are generally low ($r \leq 0.2$), with the exception of soil moisture and the WRSI in Kenya's March–May season (Figure 10). However, by mid-season, correlation co-efficients have greatly improved for soil moisture, the WRSI and the VCI. Correlations between the forecast and yield are poorer but expected, given the historic relationship between the WRSI and maize yield (Figure 7).

Moreover, the ability of forecasts to identify "drought years" correctly (those in which soil moisture, the WRSI, the VCI and yield are below their respective 20th percentiles) also improves throughout the season. Again, by mid-season, there is at least some skill (ROC-AUC > 0.6) in forecasting low (< 20th percentile) soil moisture, WRSI, VCI and yield conditions (Figure 10).

Improving forecast skill at a country level is generally consistent at the sub-country level too for both soil

moisture and VCI forecasts (Figure 12). However, some regions show a lagged response in establishing a good forecast skill. In March–May, the coastal region shows lower soil moisture and a VCI forecast skill than the rest of the country (again, possibly due to the accuracy of driving rainfall data in the region), whilst in October–December, the south of the country lags behind. However, in both seasons, these regions do improve and by the end of the season match the skill seen elsewhere.

The spatial variation in soil moisture forecast skill likely reflects differing rainfall regimes across Kenya, particularly in the Rift Valley and coastal regions which experience slightly different seasonality when compared with the rest of the country (Figure 1). The variation in the VCI forecast skill may be similarly explained or could be due to differences in vegetation type.

Incorporating rainfall seasonal forecasts

Incorporation of the SEAS5 tercile rainfall forecasts improves the skill of T-A soil moisture and WRSI forecasts. The skill gained by incorporating the SEAS5 forecasts is greater for the October–December season, suggesting that whilst the March–May season is strongly influenced by antecedent conditions (indicated by high ROC scores early in the season without incorporating the meteorological forecast), the inclusion of skilful seasonal forecasts in October–December creates an opportunity to act at the beginning of the rainy season, if there is a likelihood of drought. This extends the timeframe in which actions could be confidently triggered, therefore increasing the range of actions available for anticipatory drought management and the potential to mitigate the impacts of drought. The limited improvement in forecast skill in March–May agrees with existing research that demonstrates low predictability of the East African "long rains" (MacLeod, 2019). Incorporating seasonal forecasts in this way provides a coherent picture of drought risk, which accounts for rainfall predictions as well as the evolving condition of the land surface.

Importantly, soil moisture and the WRSI can be skilfully anticipated well in advance of the end of the season when incorporating the seasonal meteorological forecast. For March–May, low soil moisture and the WRSI (< 20th percentile) can be reliably forecast from late March and early March, respectively (Figure 10). In October–December, low soil moisture can be predicted from the beginning of the season.

Drought conditions (soil moisture and the WRSI < 20th percentile) can therefore be reliably anticipated at least two months in advance of the end of the rainy season. T-A soil moisture and WRSI forecasts are therefore able to support reliably the anticipatory drought-management decisions made during the rainy season.

4.2 | Integrating T-A into anticipatory drought-management protocols

4.2.1 | Considerations for anticipatory action based on T-A

In order to support anticipatory drought management successfully, operational drought forecasts must (1) forecast a metric relevant to the impacts of drought, (2) provide skilful predictions of drought within a timeframe that allows actions to take place and (3) include skill information on drought forecasts to build users' confidence and encourage a long-term perspective (Cash *et al.*, 2003; Lemos *et al.*, 2012; Coughlan De Perez *et al.*, 2015).

The study supports the use of T-A soil moisture and WRSI forecasts in anticipatory drought-management protocols in Kenya. The soil moisture and WRSI estimates relate closely with the impacts of drought, namely reduced pasture availability (VCI) and poor maize production, and as such are likely to align closely with food insecurity events that require humanitarian action. Furthermore, T-A forecasts are reliable ahead of the end of the season, allowing anticipatory actions to take place.

It must be noted, however, that some caution is required when designing anticipatory drought-management protocols based upon T-A soil moisture and WRSI forecasts. First, the relationship between soil moisture and pasture availability (VCI) is stronger than that of the WRSI and maize yield. Whilst not unexpected, decision-makers should be aware that the WRSI does not capture all low yield events and other factors (including pests, disease, agronomic practices and political decisions) should also be monitored to identify probable low yield events.

Second, the skill of T-A forecasts is reduced in the early season and does not extend before the season commences. However, the skill improves throughout the season and T-A forecasts become highly skilful by mid-season, although the exact timing varies between regions and seasons. Incorporating rainfall forecasts from the SEAS5 to weight the T-A ensemble improves the reliability of T-A forecasts earlier in the season, extending the period in which T-A forecasts can be considered skilful.

In addition, the skill of T-A forecasts varies spatially. For instance, soil moisture is a poor predictor of pasture availability (VCI) in Kenya's coastal region.

Temporal and spatial variation in the skill of T-A forecasts is not, however, a reason to dismiss the use of T-A forecasts to trigger anticipatory drought management for some low skill time periods or locations. Rather, skill information on T-A should be used when designing actions and triggers in drought management.

This requires a recognition that different actions each come with their own associated cost, time required for preparation and efficacy in mitigating drought impacts (Coughlan De Perez *et al.*, 2015; Heinrich and Bailey, 2020). Consideration must also be made of the cost of "acting in vain" should the forecasted drought not materialize (Coughlan De Perez *et al.*, 2015). To that end, different actions may be triggered by differing probabilities of drought and forecast skill. For instance, high-regret actions (those which incur a large cost if acting in vain) should not be triggered based upon a small increase in drought likelihood or on unskilled forecasts. On the other hand, actions that can withstand acting in vain could be triggered based upon a small increase in the probability of drought without incurring a great cost if the forecasted drought does not materialize.

Therefore, we recommend a layered approach to anticipatory drought action triggers, with different actions given different trigger thresholds at different points in the season.

In this vein, T-A soil moisture and WRSI forecasts should only be used to support potential high-regret actions from the mid-season onwards, when forecast skill is high. Nonetheless, T-A forecasts could still be used to trigger actions before, and early in, the season, so long as these actions are low risk should the forecasted drought not materialize. This may mean costly actions, such as distributing livestock food supplements and giving cash vouchers, are triggered only when forecast skill is high during the latter half of the season. Low-risk actions, however, such as sensitization around water-conservation practices and post-harvest management, could be triggered by less skilful forecasts earlier in the season. This layered approach allows action in anticipation of drought whilst minimizing potential regret should the forecasted drought not happen.

Along these same lines, triggers and actions will vary spatially based on the skill of the forecast. It may be that in some areas, such as coastal Kenya, soil moisture and the WRSI are not suitable for triggering high-regret actions at any point in the season. In such instances, T-A forecasts could be layered with alternative metrics that better represent the drought impacts in these locations. For example, efforts are currently underway to establish anticipatory drought-management triggers based on the VCI for irrigated farmland in Pakistan which does not directly respond to T-A WRSI. In other areas, however, such as the arid counties in the northwest which are particularly vulnerable to drought, skilful T-A forecasts early in the season present a real opportunity for triggering high-risk actions.

Realizing the full potential of this approach will require input from humanitarian actors (see below).

4.2.2 | From research to operations

Based on the findings of the study, efforts can now be made to integrate T-A forecasts into anticipatory drought-management protocols. Care must be taken to ensure that actions are thoughtfully matched with the forecasts and that triggers are systematically defined, considering forecast skill over space and time, and the relationship between forecast metrics and drought impacts. This will necessarily be a collaborative effort involving both forecasting scientists and humanitarian actors.

Defining appropriate actions will require humanitarian agencies to classify actions based on the costs involved, the time needed to prepare, the potential benefits of acting and the implications of acting in vain. With the constraints of T-A forecasts in mind, the appropriate actions and triggers can then be identified.

It is likely that this will be an iterative process. The present study analysed the skill of T-A forecasts in identifying events in which soil moisture, the WRSI, the VCI and yield fell to < 20th percentile. The 20th percentile was used to identify extreme droughts, or those with a one-in-five year return period. However, it may be that some anticipatory actions should be taken more often and for less severe events. The skill of T-A forecasts at a range of thresholds will need to be analysed in response to the needs of humanitarian actors. Moreover, to use the limited resources of humanitarian organizations most effectively, forecasts of biophysical drought indicators should be combined with vulnerability information to ensure that those at most risk of drought are supported.

5 | CONCLUSIONS

The study has shown that Tropical Applications of Meteorology using SATellite data—AgriculturaL Early waRning sysTem (TAMSAT-ALERT) (T-A) soil moisture and water requirement satisfaction index (WRSI) forecasts can reliably form a key component of anticipatory drought-management protocols in Kenya. Supplemented by input from humanitarian actors and layered with additional forecasting products, T-A can support humanitarian decision-making, mitigate the worst impacts of drought and ultimately improve food security. Expanding the analysis undertaken here will also allow anticipatory drought-management protocols to be scaled up to support more vulnerable populations across Africa.

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SUPPORTING INFORMATION

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