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ABSTRACT

Droughts and changing rainfall patterns due to natural climate variability and climate change, threaten the livelihoods of Malawi's smallholder farmers, who constitute 80% of the population. Provision of seasonal climate forecasts (SCFs) is one means to potentially increase the resilience of rainfed farming to drought by informing farmers in their agricultural decisions. Local knowledge can play an important role in improving the value of SCFs, by making the forecast better-suited to the local environment and decision-making. This study explores whether the contextual relevance of the information provided in SCFs can be improved through the integration of farmers' local knowledge in three districts in central and southern Malawi. A forecast threshold model is established that uses meteorological indicators before the rainy season as predictors of dry conditions during that season. Local knowledge informs our selection of the meteorological indicators as potential predictors. Verification of forecasts made with this model shows that meteorological indicators based on local knowledge have a predictive value for forecasting dry conditions in the rainy season. The forecast skill differs per location, with increased skill in the Southern Highlands climate zone. In addition, the local knowledge indicators show increased predictive value in forecasting locally relevant dry conditions, in comparison to the currently-used El Niño-Southern Oscillation (ENSO) indicators. We argue that the inclusion of local knowledge in the current drought information system of Malawi may improve the SCFs for farmers. We show that it is possible to capture local knowledge using observed station and climate reanalysis data. Our approach could benefit National Meteorological and Hydrological Services in the development of relevant climate services and support drought-risk reduction by humanitarian actors.

Practical implications

Seasonal climate forecasts (SCFs) have the potential to inform farmers in their agricultural decisions thereby improving preparedness to droughts. However, barriers remain in the uptake of SCFs to decision-making. Local knowledge can play an important role in improving SCFs as it may lead to SCFs that are better suited to local environmental and decision-making contexts. Integrating SCFs and local knowledge may be better understood and trusted by local users, leading to a better uptake of SCFs.

However, using local knowledge to inform the choice of indicators in seasonal forecast systems and using local knowledge to validate seasonal forecasts remains inadequately explored. This study has therefore characterised the local knowledge through focus group discussions, where we ask farmers how they forecast drought and how they define drought conditions. Subsequently, the local knowledge is linked to long-term observation data and used in a

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scientific drought forecasting model. The results show that at some locations of local knowledge forecasts can successfully forecast locally relevant dry conditions; the timing of the onset of rain and the number of dry spell occurring the rainy season. The local knowledge indicators can complement indicators commonly used in drought forecasting, such as the El Nino-Southern Oscillation (ENSO).

Local knowledge and forecast models can work together more closely (e.g. to shape what meteorological data is collected, how forecast models are designed, how forecasts are communicated, etc.). Integrating local knowledge in the co-production of SCFs could be an effective tool to achieve this (Kalanda-Joshua et al., 2011). The trust and uptake of information by farmers could be enhanced by alligning the content and timing of SCFs to the local knowledge of farmers (Alessa et al., 2008; Kniveton et al., 2015). Taking farmers is important to take farmers own expectations about the upcoming rainy season into account is therefore very important when communicating a forecast, particularly when they contradict local expectations (Nkomwa et al.,2014).

In some areas of climate services there is a potential in bringing together and accessing the skill of different predictors for different purposes. For the agricultural sector the onset of rain and dry spells are important predictands and local knowledge based indicators could enhance these forecasts. In addition, local knowledge predictors can be included in ongoing drought forecasting efforts. Examples of efforts include anticipatory forecast models and phased approaches in early action protocols for humanitarian agencies.

There are concerns that the value of local knowledge is being eroded by the increased variability and unpredictability due to climate change and investments in conventional SCFs approaches (Plotz et al., 2017). This study, however, found that with a recent dataset the meteorological indicators may have a predictive value. These findings suggest that, despite climate change, meteorological indicators based on local knowledge are not decreasing in its reliability. On the contrary, it could even create opportunities in a changing and more unpredictable environment.

1. Introduction

Throughout sub-Saharan Africa, more than 95% of cultivated land is devoted to rainfed agriculture (Wani et al., 2009). This is a production system that is vulnerable to climate variability. Droughts and frequent dry spells can reduce crop yield and lead to food insecurity (Ibrahim and Alex, 2008). Climate change is projected to aggravate the effects of climate variability, causing more erratic rainfall and an overall increase in temperature (Winsemius et al., 2014; Ziervogel et al., 2014), even for low-emission scenarios (Engelbrecht et al., 2015).

Both climate information and the local knowledge of farmers can have an instrumental role within adaptation and reduce vulnerability to drought (Tschakert and Dietrich, 2010). Here we adopt FAO's definition of local knowledge as "a collection of facts related to the entire system of concepts, beliefs, and perceptions that people hold about the world around them. This includes the way people observe and measure their surroundings, solve problems, and validate new information. It includes the processes whereby knowledge is generated, stored, applied and transmitted to others." (FAO, 2005). As the continually evolving product of interaction and exchange, we recognize that local knowledge is diverse and hybrid. Whilst distinct from, it may not fully be independent of the knowledge developed within more formal academic or research institutions. In addition, local knowledge of climate variability is deemed important as it reflects local conditions and concerns (Danielsen et al., 2005) and focuses on the actual impacts of climate variability on people's lives (Laidler, 2006).

Seasonal climate forecasts (SCFs) can inform the agricultural decisions farmers take, thereby improving preparedness for droughts (Hansen et al., 2011). However, barriers remain in the uptake of SCFs in decision-making (e.g. Tadesse et al., 2015; Christel et al., 2018). SCFs are often not sufficiently representative at a local scale (i.e., high resolution) and are, therefore, not applicable to the local context (Bruno Soares et al., 2018). This may lead to information that is not trusted or applicable for the farmers. Moreover, SCFs are sometimes not usable or applicable as they are not clearly linked to actionable information (Patt and Gwata, 2002). Appropriate and sustained engagement with users is required for climate service providers to understand and respond to their users' needs (Tall et al., 2014). This realisation typically manifests in calls for providers to involve users in co-design and co-evaluation of information products and services, and to develop effective communication mechanisms (Mittal et al., 2021; Vincent et al., 2020). Local knowledge can play an important role in improving the utility of SCFs (Kniveton et al., 2015) by ensuring they are better-suited to local environmental and decision-making contexts, as well as being better-understood and trusted by local users (Plotz et al., 2017; Andersson et al., 2020). Local knowledge includes different categories, such as ecological (e.g. flora and fauna), celestial (e.g. star positions), or meteorological (e.g. wind processes, sensible temperature feelings, and rainfall and observations of clouds) observations (Trogrlić et al., 2019). Most approaches in the literature focus on the local knowledge indicators under the meteorological category.

A variety of approaches have been used to integrate local knowledge with SCFs in different studies. Plotz et al. (2017) proposed a decision-framework for choosing the most appropriate method to combine SCFs and local knowledge. This includes the 'consensus approach' whereby an 'agreed upon' final forecast is built on both local knowledge and a forecast based on contemporary scientific information (e.g. Guthiga and Newsham, 2011; Kolawole et al., 2014; Dube et al., 2016). Another approach is the 'science integration approach' and is typically based on collecting data on local knowledge forecasts to create a mathematical model or formula (e.g. Mackinson, 2001; Waiswa et al., 2007; Masinde, 2015; Mwagha & Masinde, 2015; Nyadzi et al., 2020; Gbangou et al., 2021)). The latter approach has the advantage that, if this conversion and combination is possible, the forecast can be up-scaled to more regions beyond that of the original knowledge holders. The ability to expand means that the likelihood of combined forecast continuity is greater (Plotz et al., 2017). However, using meteorological local knowledge to inform the choice of indicators in seasonal forecast systems and using local knowledge to validate seasonal forecasts has been inadequately explored.

Following the scientific integration approach, this study characterises the local knowledge of farmers in central and southern Malawi through focus group discussions. Their responses are then used to inform the predictors and the predictands of a drought forecast model and evaluate the predictive value of this model.

2. Methods

2.1. Case study central and Southern Malawi

The study focuses on three districts in Central and South Malawi: Salima, Mangochi, and Zomba (Fig. 1a). The criteria for selecting the districts were: area under rainfed maize cultivation, previous experiences of drought and flood, high food insecurity risk (World Bank, 2009), and the presence of excisting climate services programmes. We refer to Mittal et al., 2021 for a detailed justification of the selection of the research locations. The Department of Climate Change and Meteorological Services (DCCMS) has meteorologically divided Malawi into five climate zones: Northern Areas, Central Areas, Lakeshore Areas, the Southern Highlands and the Shire Valley (Fig. 1b). The research locations are in the Lakeshore Areas and Southern Highlands. There are six weather stations located in the Lakeshore Areas, and five stations in the Southern Highlands (Fig. 1b). Fig. 1b also shows the digital elevation model (DEM) and locations of these eleven weather stations. For the

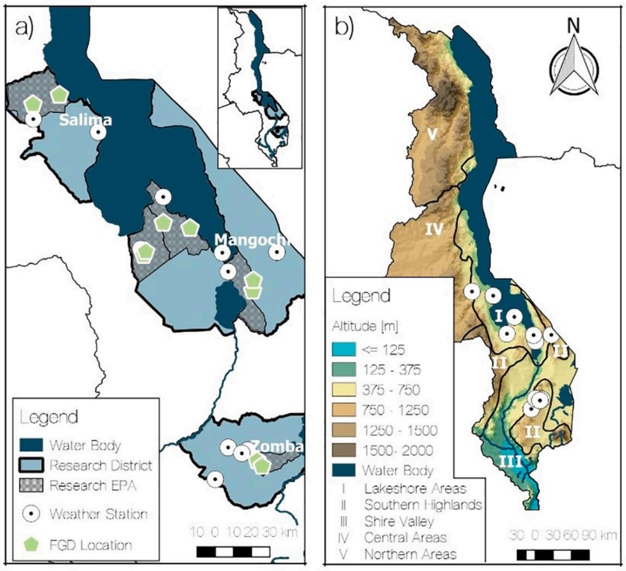

Fig. 1. a) Research Areas b) Climate Zones and Digital Elevation Model.

provision of SCFs, DCCMS has divided Malawi into two parts; the northern and southern half of the country which are influenced differently by El Niño Southern Oscillation (ENSO). The rainy season is approximately from November to April, in which 95% of the annual rain falls. This means rainfed-agriculture is not practiced in the dry season and people are predominantly reliant on the rainy season for domestic crop production (Coulibaly et al., 2015).

Malawian households have a long history of adapting to droughts using traditional and emerging practices (Tschakert and Dietrich, 2010). Based on their study in Chikwawa in Southern Malawi, Nkomwa et al. (2014) indicate that communities can recognise the changes in climate and local environment. Examples of changes include delayed and unpredictable onset of rainfall, declined rainfall trends, increased temperatures and increased frequency of prolonged dry spells in the region. In southern Malawi, Chidanti-Malunga (2011) found that when a drought is expected, farmers introduced a variety of adaptation measures, including mulching, pit planting, crop diversification, managing of residual moisture, shifting of planting dates and seeking alternative sources of income. However, Kalanda-Joshua et al. (2011) found that current scientifically-based weather and climate predictions in Malawi are not widely used to inform adaptive decision making. The authors attribute the unuse to a lack of integration of local knowledge in those forecasts.

In Malawi, maize is a staple crop. In our research districts, farmers allocated the largest proportion of their agricultural lands to the production of maize. Other crops included cotton, rice, groundnuts, sweet potatoes, tobacco, sorghum and pigeon peas. Farm sizes vary between 0.4 and 2.4 ha, with a majority of farm sizes between 0.6 and 1.2 ha.

2.2. Qualitative data collection on local knowledge

Qualitative data were collected to understand local practices and identify meteorological indicators within local knowledge. Ten participatory focus group discussions (FGDs) were held with smallholder farmers in the Salima (2 FGDs), Mangochi (6 FGDs), and Zomba (2 FGDs) district, see Fig. 1(a). In Malawi, districts consist of several Extension Planning Areas (EPAs). Two FGDs were held for each EPA: Khombedza (Salima), Nankumba, Mbwadzulu and Maiwa (Mangochi), and Mpokwa (Zomba). The FGDs were performed in collaboration with the study of Mittal et al., 2021, who identified agro-climatic indices that can inform agricultural decisions of maize-growing farmers. There were 70 female and 48 male farmers who took part in the FGDs. The facilitator of the FGDs was a local research assistant, holding the discussions in Chichewa, the local language. The facilitator also transcribed and translated the recordings into English. Mittal et al., 2021 gives more information on the protocol used, participant characteristics, the choice of sampling and research locations.

The focus of this study was to characterise:

i) Predictands – what weather conditions (during the rainy season) do farmers perceive as dry to inform their decision-making?
ii) Predictors – what meteorological observations (before the rainy season) do farmers make to predict dry conditions (during the rainy season) as part of their local knowledge to inform their decision-making?

In the focus group discussions, participants completed two seasonal calendars, addressing specific topics throughout the year. The first seasonal calendar included: 1) weather conditions related to a good rainfall season; 2) weather conditions related to a poor rainfall season; 3) other conditions related to a good or bad rainfall season (e.g. changes in flora and fauna). In the second calendar, the participants were asked to identify an extreme drought year and discuss weather conditions during that year in detail.

Transcriptions of the FGDs were analysed through coding of interviews and categorising the responses into the categories of local knowledge as explained in the introduction. The results provide insights into available local knowledge of the farmers throughout the year. This includes knowledge of ecological (e.g., mango trees and bird species), celestial (e.g., sun and moon positions) and meteorological indicators (e.g., wind direction, sensible temperature). In this study, we solely included knowledge related to the meteorological indicators as we focus on how local knowledge can add context to seasonal climate forecasts. Further details on ecological and celestial indicators found in this research can be found in Streefkerk (2020), Appendix C. We used the transcription of the meteorological local knowledge to link meteorological indicators (predictors) and dry conditions in the rainy season (predictands) to in-situ observations and reanalysis data (see method Section 2.3.2).

2.3. Quantitative data collection on predictors and predictands

Both the knowledge of the farmers and the SCFs produced by DCCMS rely on meteorological indicators for forecasting drought conditions. In this research, both types of meteorological indicators are used to predict dry conditions, and compared with one another. The meteorological indicators and the computation of the dry conditions are based on observed and reanalysis data.

Table 1 provides an overview of the data sources of the conditions during the rainy season considered as dry (predictands) and the meteorological indicators (predictors) identified. We note that the choice of predictands and predictors is based on the results of the qualitative data collection from the FGDs. There are eleven stations across two climate zones, though the period of record differs per station (see Supplementary Materials Tables A1-2 for further details). The seasonal climate forecast by DCCMS mostly relies on the ENSO phenomenon, and ENSO is therefore included in this study (Cash et al., 2006) and quantified by the Oceanic Nino Index (ONI). The ONI dataset is obtained from the National Oceanic and Atmospheric Administration (NOAA) and span form 1950 to 2018 (NOAA, 2019). ERA5 is a gridded climate reanalysis dataset from the European Centre for Medium-Range Weather Forecasts (ECMWF) (Muñoz Sabater, 2019). The hourly ERA5 data have a 0.25° × 0.25° horizontal resolution and span from 1979 to 2019. The common period of analysis is from 1979 (start of ERA-5 data availability) and 2016/2018, depending on the availability of weather station records.

Table 1
Dry conditions (predictands), meteorological indicators (predictors), and their data sources.

	Based on	Data Variable	Source	Temporal Resolution	Spatial Resolution
Predictands					
Dry Conditions	Local knowledge	Rainfall	DCCMS Observations	1889–1980 to 2012/2019 (differs per station). Daily.	Point observation
Predictors					
Wind	Local knowledge	Wind speed & direction	ERA5 Reanalysis data	1971–2019. Hourly.	0.25° x 0.25°
Temperature	Local knowledge	Minimum & Maximum Temperature	DCCMS Observations	1961/1983 to 2005/2019 (differs per station). Daily.	Point observation
		Relative Humidity	ERA5 Reanalysis data	1971–2019. Hourly.	0.25° x 0.25°
ENSO	DCCMS	ONI	NOAA	1950–2018. Monthly.	Point observation

2.3.1. Linking meteorological data with local knowledge

The qualitative data on farmers' local knowledge on drought (both predictands and predictors) is matched with the quantitive datasets presented in Table 1.

2.3.1.1. Dry conditions (predictands). Farmers aim to predict dry conditions (predictands) to inform their decision making. During the FGDs, the farmers provided qualitative descriptions of what dry conditions (predictands) entail. For the sake of the explanation of the methodology, we already express here what the dry conditions (predictands) are: timing of the onset of rain, the number of dry spells and an overall indication of the severity of drought in the rainy season. Here, farmers describe drought as a rainy season with (a combination of) dry conditions when wet conditions would be expected, i.e. short rainy season, late onset of rain, dry spells, few rainy days, low total rainfall. As a first step, the conditions identified by the farmers and considered as dry are used to construct a set of indicator variables that are derived from rainfall observations, and further specified based on literature (see Table 2).

To facilitate further analysis, the indicator variables in Table 2 are expressed as dry conditions that can inform farmer's decision-making (predictands). The description of historical drought events by the farmers in the second calendar developed in the FGD are compared to timeseries of these indicator variables (effective planting onset and number of dry days) calculated from the rainfall data at each of the eleven stations. An iterative process of comparing the indicator variables and the drought events described during the FGDs was used to define the parameters in the definition of the dry conditions (predictands): number of dry spells, timing of the onset of rain and the drought index (Table 3). A 'drought index' was additionally established to represent a composite measure of dry conditions in the rainy season at larger scale. The drought index is computed by a Principle Component Analysis (PCA) which statistically derives a number of 'principle components' of the (inverse) normalised variables to explain the variance in the dataset (e.g. (Arabzadeh et al., 2016)). The drought index is determined using the first principle component and its coefficients (see Table 3). The first principle component explained 46.9% of the variance and has a Kaiser-Meyer-Olkin (KMO) measure of 0.57. Adding a second principle component would include negative coeffients in the drought index and be in contradiction with the farmers' perceptions of dry conditions. The drought index is continuous and always positive; the higher the drought index, the more extreme the drought is considered to be. The final definitions of the predictands and the thresholds used in the forecast model are presented in Table 3. The timing of the onset and the number of dry spells are computed for each station, while the drought index is computed for each the two climate zones using precipitation interpolated from the stations using Thiessen polygons.

Table 2
Definitions of indicator variables used to construct the Dry Conditions

Indicator variable	Definition
Length of Rainy Season	The difference in days between the onset and end of the rainy season (Liebmann and Marengo, 2001).
Effective Planting Onset	A period of t days that exceeded the threshold of more than × mm, not followed by a dry spell of n days in the next c days (Stern et al., 1982). ($t = 3$ days, $x = 25$ mm, $n = 1$ day, $c = 5$ days)
Number of Rainy Days	The sum of the number of rainy days. A rainy day is defined as a day that exceeds a rainfall threshold value of 2 mm (Savenije, 2004).
Total Rainfall	The sum of all rainfall within the 'length of the rainy season'.
Number of dry days	The cumulative number of 'dry days' (Mittal et al., 2021). A dry day is a day with <2 mm (Savenije, 2004).

Table 3
Definitions of Dry Conditions (predictands)

Dry Condition	Level	Definition	Forecast thresholds
Timing Onset of Rain	Station	Days after 1st of October of 'Effective Planting Onset'	+5, +10, +15, +20 and +25 days later than the average onset of rain
Number of Dry Spells	Station	Amount of 'Dry spells'. 'Dry spell' defined as 5 or more 'number of dry days'.	2, 3, 4 and 5 dry spells
Drought Index	Climate Zone	Drought index = α•'Number of Rainy Days' (inverse normalised) + β•'Total Rain' (inverse normalised) + γ•'Length Of Rainy Season' (inverse normalised) + δ•'Effective Planting Onset' (normalised) + ε•'Number of Dry Spells' (normalised). (α=0.882, β=0.76, γ=0.756, δ=0.522 ε=0.113)	55^{th}, 60^{th}, 65^{th}, 70^{th} and 75^{th} percentile

2.3.1.2. Meteorological indicators (predictors). The meteorological indicators that are based on local knowledge (Table 1, predictors) are compared to the dry conditions (Table 3) to identify distinctive patterns that can be used in the forecast model. This is done through time series analysis of the data variables at each station (or single grid cell in which the station falls) for the years that are discussed during the second calendar of the FGD. This linking allows us to investigate whether there are temporal patterns that resemble the meteorological indicators from local knowledge and can be used as predictors in the forecast model. The wind-related local knowledge is expressed in two indicators: wind speed and direction. In addition to the time series analysis, a spatial analysis is done by visual presentation of larger-scale wind processes at grid level, representing North and South Easterly winds with respect to the FGD locations. Wind direction was one of the meteorological indicators mentioned by the farmers (Sections 3.1 and 3.2). The local knowledge related to temperature is expressed in three indicators: minimum and maximum temperature, and relative humidity. Relative humidity is taken into consideration due to mention by farmers of thermal sensation. For example, the feeling of 'hot' may be explained by a high relative humidity (Berglund, 1998).

2.4. Model setup and analysis

Our threshold model relates monitored meteorological indicators based on wind direction and wind speed, temperature, and relative humidity anomalies and ENSO *before* the rainy season (June to November), to the occurrence of dry conditions *during* the season (November to April). The objective of the model is to determine whether meteorological indicators informed by local knowledge (temperature and wind) have skill in forecasting dry conditions at a range of monthly lead times (June to November).

For every year in the available datasets (given in Table 1), we calculate monthly aggregates of the meteorological indicators (wind, temperature and ENSO) for the dry season months (June to November) prior to the rainy season of interest (November to April). Dry conditions as defined by the timing of the onset of the rain, number of dry spells, and the value of the drought index within that rainy season are calculated for every year in the dataset. The dry season is the period when farmers make predictions about the upcoming rainy season, and observe wind and temperature-related local knowledge indicators. These predictions may inform agricultural decisions they take in the dry season prior to the coming cropping (rainy) season (e.g. choosing seed/crop types, land preparations). Once they have made decisions in the dry season, it is hard to adapt or reverse their decisions as they have already invested (either in time or in money).

The forecast model is applied at several lead times before the start of the rainy season, where the predictors are incorporated depend on the lead time that is provided. For example, the forecast at a lead time of three months (August), includes the indicators of June (start of new cropping season), July, and August. Fig. 2 shows the dry and rainy seasons, the lead times, and the time windows within which the dry conditions occur (as expressed by the farmers, see Section 3.1).

As a 'pre-processing' step, and to determine which meteorological indicators are suitable as predictors, a pair-wise correlation analysis was done. The meteorological indicators (Table 1, predictors) were correlated one by one with each of the three different dry conditions (Table 3) using the Spearman Rank method to find the significantly correlated indicators ($|r|$ greater than 0.25) at the p-value of $p < 0.075$. Significantly correlated indicators are then selected as inputs for the forecast model. The correlations may differ per rainfall station and this analysis enables us to identify which predictors are relevant for each location.

The meteorological indicators (predictors) are separated into three categories: wind, temperature and ENSO (Table 1, predictors). Wind and temperature indicators are included as these were extracted from farmers' local knowledge during the FGDs, while ENSO is a commonly used predictor in drought forecasting. For every meteorological indicator, a separate predictor threshold is set that indicates whether it predicts drought. In particular, when the meteorological indicator value exceeds the corresponding threshold, we set the indictor to 1, showing that drought conditions are predicted. When the meteorological indicator value is below the threshold, we set the indictor to 0, showing that drought conditions are not predicted. To ensure an equal participation of the predictors in the three categories, the resulting ones or zero are averaged per wind, temperature or ENSO category. If the majority indicators predicted a drought (total average of the categories greater or equal to 0.5) the final binary output for the predicted event will be set to 1 (=predicted drought), otherwise 0 (=no predicted drought).

Observed drought is identified as when the dry conditions (Table 3) as calculated using observed rainfall data exceeds the set drought threshold (=1) or not (=0). The drought thresholds of the dry conditions can be varied to find the performance of the meteorological indicator for different 'severities' of drought (see Table 3). For the drought index the thresholds are the 55th, 60th, 65th, 70th and 75th percentiles. For the timing of the onset the thresholds are +5, +10, +15, +20 and +25 days later than the average onset of rain at a station. For the number of dry spells the thresholds are 2, 3, 4 and 5 dry spells (or more).

The best set of threshold value combinations for the predictors is found by a global optimization method called 'Differential Evolution' in the SciPy environment of Python (Storn & Price, 1997). The model minimizes a goodness of fit function, expressed as the mean absolute difference between the predictions (P) and observations (O). Commonly known as mean absolute error (ME), whereby N represents the length of the yearly dataset per station or climate zone (that differs for each location):

$$ME = \frac{1}{N}\sum_{i=1}^{N}|(P_i - O_i)|$$

The forecast model eventually gives a binary outcome that represents the predicted events for every year (drought=1, no drought=0). For each model which has at least two predictors, the following analysis steps are performed:

i. The best predictors are ranked and selected based on the computed mean error (ME), for each location and dry condition (predictand).

ii. Leave one-out (LOO) and k-fold ($k = 5$) cross validation. Both validation methods are performed to ensure we do not train and evaluate the model using the same data. The LOO maximises the amount of training, but can be susceptible to autocorrelation in the time series. The repeated k-fold method uses less training data, but is less susceptible to effects of autocorrelation.

iii. Analysis of the performance of the validated models by calculation of Heidke Skill Score (HSS). HSS is a measure of proportion correct over the chance forecast (Heidke, 1926) and is computed as follows for a standard 2x2 contingency table (TP = True Positives; TN True Negatives; FP False Positives; FN False Negatives)

$$HSS = \frac{2((TP \cdot TN) - (FP \cdot FN))}{(TP + FN)(FN + TN) + (TP + FP)(FP + TN)}$$

The HSS ranges from $-\infty$ to 1. Negative values indicate no skill, meaning that a chance forecast is better. Scores between 0 and 1 indicate skill. A perfect forecast has a score of 1.

iv. Bootstrapping (n=1000) of the HSS by resampling the scores of

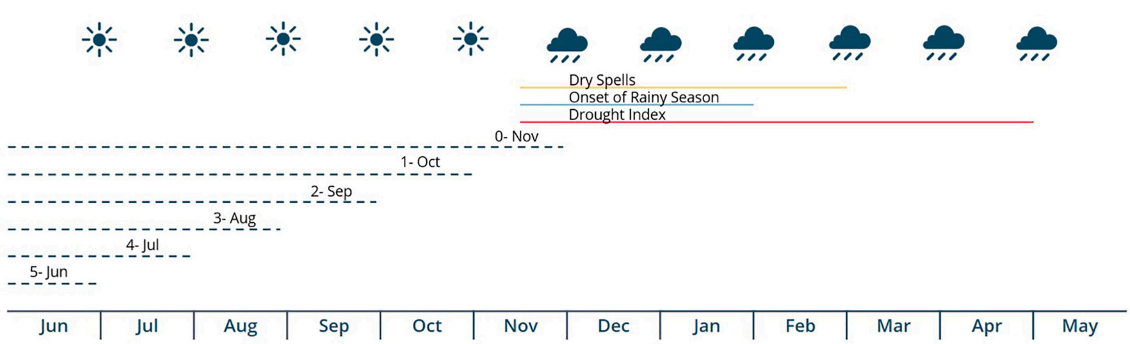

Fig. 2. Visual representation of lead times. The lead times are defined as the number of months before the start of the rainy season. The sun symbols represent the dry season and the clouds with rain symbols the rainy season. The dashed lines represent the period for which predictors are used in the forecast model for the given lead time.

the cross-validated models. The 5th and 95th percentiles are obtained as confidence intervals of the scores.

3. Results

3.1. Local knowledge on forecasting dry conditions

Farmers have local knowledge in predicting dry conditions in the rainy season. Farmers expressed dry conditions in terms of the variables they use for their agricultural decision-making: the timing of the onset of rain, the occurrence of dry spells and a seasonal outlook on the occurrence of drought. The onset of the rains typically occurs mid-November. However, during dry years the onset of the rains that is effective for planting may be extended to January. The occurrence of dry spells may start from the onset of the rainy season to February. Farmers explained drought as a rainy season with dry conditions when there should be wet conditions, i.e., short rainy season, late onset of rain, dry spells, few rainy days, and low total rainfall. Information on these dry conditions may inform various decisions such as the timing of planting and land preparations, and what type of seeds to plant or ridges to make. Streefkerk (2020) contains a more elaborate analysis on how predictions of dry conditions can inform agricultural decisions.

Both wind and temperature observations are part of the farmers' knowledge on the prediction of dry conditions. Wind indicators are expressed as a deviation in direction and severity from what is expected during normal conditions. 'Mwera' winds are strong South Easterly winds, typically occurring from June to July. When they occur from September to November, dry conditions are expected in the rainy season. The wind indicators often coincide with the temperature indicators. When winds are mentioned, mostly the relative temperatures are mentioned as well; "*When there are **cold winds** in October or November, we know that rains will delay." (Female farmer, FGD location Maiwa, Mangochi).* Temperature indicators are described as a relative feeling, compared to what is considered the normal temperature of that month. It should be relatively cold from June to half of August. If it is very hot in June, people are already expecting it to be cold in October, which indicates dry conditions in the rainy season. An overview of the 'normal' conditions and when dry conditions are expected is given in Fig. 3. Overall, there was a consensus on the relations between the wind and temperature conditions in the dry season and rainfall conditions in the rainy seasons for all study locations. The wind and temperature indicators forecasting dry conditions were mentioned 45 times in total.

3.2. Linking local knowledge to scientific data

3.2.1. Identifying predictors and predictors

Table 4 gives some example quotes from the FGD transcripts of how local knowledge of the farmers is linked to different predictors and predictands. These examples are included because of their clear description of meteorological indicators (predictors) and dry conditions (predictands) and the diversity of predictor-predictand relations.

Table 4
Examples of the linkage between local knowledge and different predictors and predictands

Local knowledge of farmers during FGD	Meteorological Indicator (Predictor)	Dry Condition (Predictand)
"When in September and October and we have **little winds**, it is a sign that we will have **rain on time**. But when it is windy, chances of good rains are minimal."	Wind speed	Timing onset of rain
"Heavy winds in October and November is an indication that there will be **erratic rains** in that season. Especially when we experience whirlwinds."	Wind speed	Dry spells
"If we have **Mwera winds** blowing heavily in October up to November, we expect a **dry spell**. And North Easterly winds are a sign of good rains. Mwera winds block the Northeasterly wind."	Wind direction	Dry spells
"If we experience **high temperatures** in June, we start having doubts to say, if it is this hot in June, what will October bring us? Usually in this case, we have **low temperatures** in October. This is a sign that we will **not have adequate rainfall**."	Minimum, maximum temperature, relative humidity	Total rainfall, rainy days (drought season)
"The month of July is normally **cold**. But when we see that it is sunny and the **temperatures are high**, we expect the **worst**."	Minimum, maximum temperature, relative humidity	Drought season
"Early august, it is **cold to warm**. The temperatures then rise the second half of the month. But when we see that it is cold throughout the month, it is a sign that **rains will delay**."	Minimum, maximum temperature, relative humidity	Timing onset of rain
"When we have **cold weather** in October and November, we look forward to a **dry spell.** But when we have **high temperatures**, we know for sure that it will rain."	Minimum, maximum temperature, relative humidity	Dry spell

3.2.1.1. Dry conditions (predictands)

The predictands are expressed in terms of various dry conditions that are related to rainfall. The predictands include the timing of the onset of rain (e.g. '*rain on time*', '*rains will delay*'), the occurrence of dry spells (e.g. '*erratic rains*', '*dry spell*') expressed as the number of dry spells, or an overall indication of the season (e.g. *'the worst', 'not adequate rainfall', 'erratic rains')* expressed as the drought index. The computation and definitions of the predictands is previously explained in section 2.3.2.

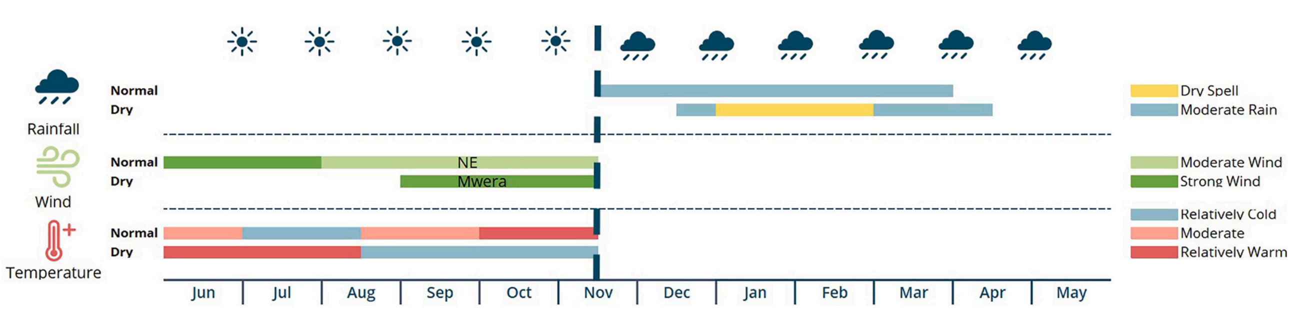

Fig. 3. Conditions before and in the rainy season during normal and dry conditions, according to farmers. NE = North Easterly winds. Mwera = strong South Easterly winds.

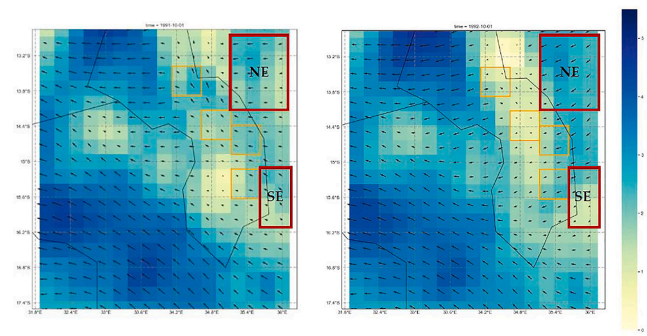

Fig. 4. Spatial selection of 'North Eastern (NE)' and 'South Eastern (SE)' regions. In these NE and SE regions, we analyzed the wind direction and speed. Left shows a 'dry' year (high drought index) and right a 'normal' year (average drought index). The FGDs took place in the four squared boxes. The size of the grid represents 0.25° by 0.25° (~30 by 30 km).

3.2.2.1. Meteorological indicators (predictors). The predictors are expressed as local knowledge on temperature and wind (see Table 3). The predictors are aggregated to a monthly time step, as the local knowledge is expressed on a monthly scale (e.g. *in **September and October** we have little winds)*. For local knowledge related to temperature, relative humidity, minimum and maximum temperature are taken into consideration. For local knowledge related to wind this includes wind direction and speed. Fig. 2 shows an example of how large-scale wind processes are visually assessed and linked to local knowledge. In the FGDs farmers expressed the *mwera* winds as a strong South Easterly wind, both referring to the direction and the speed component of the wind. The visual representation of large-scale wind processes of historical *dry* and *normal* year (from FGDs) allows the selection of spatial NE and SE regions (Fig. 4). The average wind speed and direction of the NE and SE regions are incorporated as predictors in the analysis and models, together with the wind indicators at the location of the stations at climate zones.

3.3. Forecast model

3.3.1. Correlations between predictands and predictors

In this section the links between the predictands and predictors are elaborated on. Table 5 gives an overview of the Spearman Rank correlation results for different predictands and predictors. Predictors that have at least two significant correlations with a predictand are included in Table 5. The wind speed and wind direction predictors in Table 5 represent all measured locations (both at station locations and the large NE and SE regions). Supplementary Materials Tables B1-5 give a more detailed overview.

Both wind and temperature predictors are included in predicting the *number of dry spells* during the rainy season. The (monthly mean daily) maximum and minimum temperatures are negatively correlated with an increased number of dry spells. For maximum temperature, this association is found only in the Southern Highlands region during the months July to November. Relative humidity is positively correlated with dry spells in the months July to November. For wind-related predictors, wind speed has a negative correlation for the month November, while both wind speed and wind directions have positive correlations from June to September.

The (monthly mean daily) maximum temperature, relative humidity, and wind speed correlate positively with the *timing of the onset of train.* These predictors are corroborated by local knowledge. Maximum temperatures during the dry season are positively correlated with the (delayed) onset of the rainy season. Relative humidity shows negative correlations in the months September to November, while for one station it is positively correlated in August. Wind speed in different regions (at station, NE or SE region) show correlations with the timing of the onset of rain. Wind speed has negative correlations in June to August, and positive correlations in September to November.

The correlation results for the *drought index* show that the ENSO related predictor, ONI, is an important indicator of drought in both regions. This contrasts with the previous results of the onset and dry spells where the predictors informed by local knowledge showed more and stronger correlations; here, only one 'local knowledge' predictor, wind speed in June, shows significant negative correlations with the drought index.

3.3.2. Performance of models

In Figs. 5–7, the performance of the models is illustrated, for different lead times before the rainy season and thresholds of dry conditions (such as onset). The performance is expressed as the Heidke Skill Score (HSS) for the k-fold cross validation. The HSS for the LOO cross validated models can be found in Supplementary Materials Figs. C1-3. The models show skill in some cases; however, the performance differs per station, dry conditions, threshold, and lead times. Skilful forecasts are observed when the HSS is above zero, including the 5th and 95th confidence intervals. If there are not two or more predictors (significant correlations) at a certain lead time or station, the scores for that lead or station are empty.

Out of the eleven stations, nine stations had two or more predictors for the *number of dry spells* predictand as shown in the yellow plots in

Table 5
Spearman Rank Correlation Results between the different predictands (dry conditions) and predictors (meteorological indicators). The column # corr. indicates the number of stations that have significant correlations with the predictor in the climate zones (SH = Southern Highlands, LA = Lakeshore Areas)

Predictand	# corr.	Predictor	June	July	Aug	Sept	Oct	Nov
Number of Dry Spells	SH (5/5) LA (0/4)	Max. temp.		**−0.47 –0.68**	**−0.40**	**−0.47**		**−0.33 −0.35**
	SH (4/5) LA (2/4)	Rel. hum.		**+0.51 +0.36**	**+0.54**		**+0.22 +0.37 −0.34**	**+0.29 +0.31**
	SH (3/5) LA (2/4)	Min temp.				**−0.27**	**−0.19**	**−0.26 −0.18 −0.42**
	SH (4/5) LA (3/4)	Wind speed	**+0.33**	**+0.33 +0.34**	**+0.54**	**+0.40 +0.30**		**−0.42 −0.41 −0.36 −0.43 −0.29 −0.30**
	SH (2/5) LA (2/4)	Wind direction	**+0.31 +0.32**		**+0.42 –0.32**	**+0.32**		
Timing of Onset	SH (4/5) LA (1/5)	Max. temp.	**+0.35 +0.48 +0.33**		**+0.33 +0.43**	**+0.43 +0.41**	**+0.45 +0.35**	**+0.35 +0.69**
	SH (4/5) LA (4/5)	Rel. hum.			**+0.35**	**−0.40**	**−0.33 −0.43**	**−0.46 −0.30 −0.49 −0.41 −0.41**
	SH (5/5) LA (5/5)	Wind speed	**−0.44 −0.46 −0.44 −0.37 −0.31 −0.33**		**−0.53 −0.55**		**+0.34 +0.35 +0.30**	**+0.30 +0.42 +0.29 +0.33 +0.38 +0.34 +0.29**
Drought Index	SH (1/1) LA (1/1)	ONI	**+0.36 +0.45**	**+0.35 +0.45**	**+0.29 +0.41**	**+0.39**	**+0.27 +0.38**	**+0.28 +0.37**
	SH (1/1) LA (1/1)	Wind speed	**−0.33 −0.30 −0.37**					

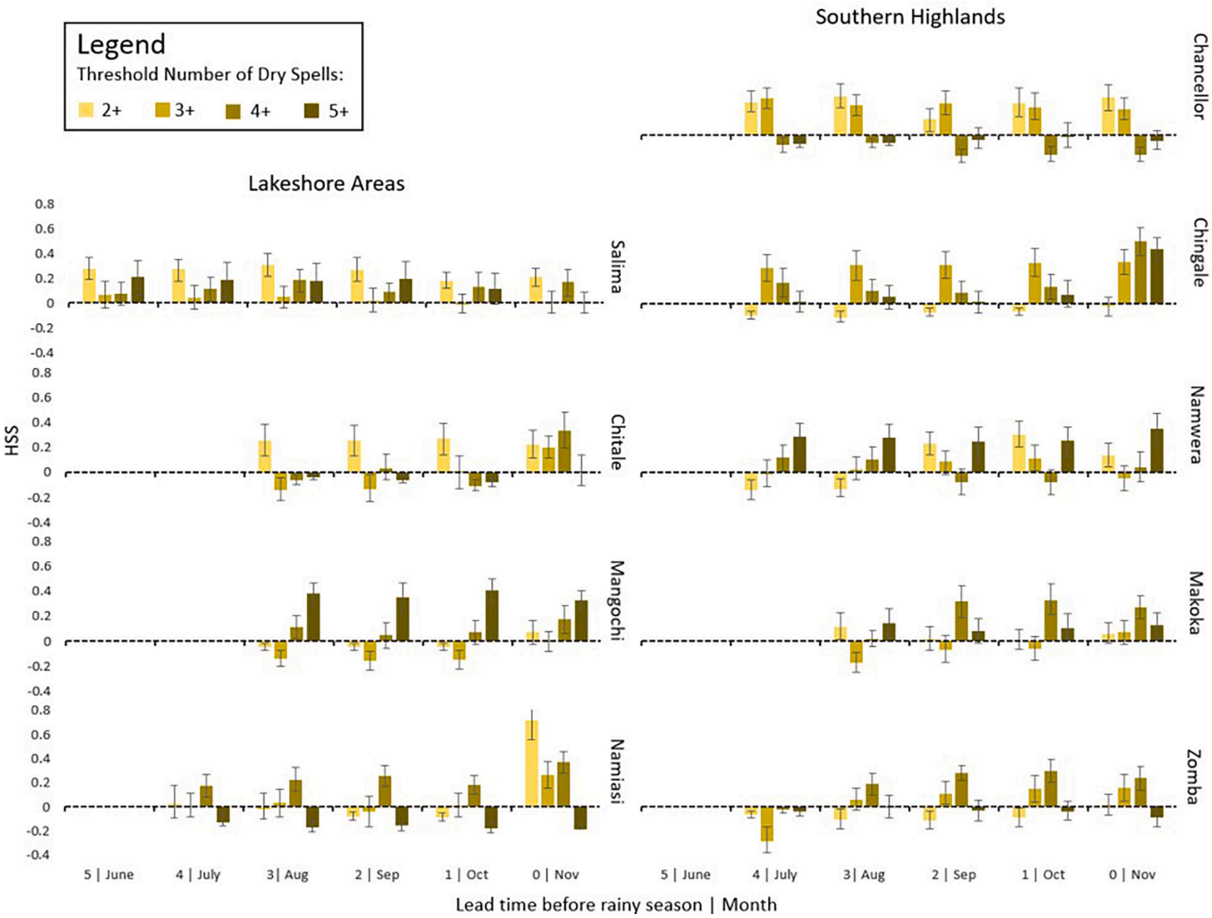

Fig. 5. Heidke Skill Score (HSS) of k-fold cross validation results for stations in Lakeshore Areas (left) and Southern Highlands (right), at different thresholds for number of dry spells (2+, 3+,4+ and 5+). The error bars indicate the 5th and 95th percentiles of the HSS. Skilful forecasts are observed when the HSS is above zero, including the error bar.

Fig. 5; the two stations with less than two predictors are located in Lakeshore Areas (Monkey Bay and Nankumba). Most models perform well for only one or two thresholds and it differs per station which threshold that is. One out of nine stations (Salima) has skilful results (for at least one threshold) by June (longest lead time), five by July, and all stations by August..

Fig. 6 shows the results of nine stations for the predictions of the *timing of the onset*. Two stations in the Lakeshore Areas climate zones do not meet the requirement of having two predictors and are therefore not included in the figure. Four out of nine stations have skilful results (for at least one threshold) by June (longest lead time), five by July and August, and seven stations by September. The stations at Namiasi and Nankumba in the Lakeshore Areas do not have skilful results for any lead time.

For the predictand *drought index* skilful forecast can be observed for all lead times in both climate zones, as can be observed in Fig. 7. For forecasts in the Lakeshore Areas not all thresholds can be forecast skilfully. The 65th and 70th percentiles can be forecast skilfully across all lead times, while for the 55th and 60th percentiles it cannot. The forecast for Southern Highlands show skilful results at all lead times for the 55th, 60th, 65th and 70th percentiles. There are no skilful results for the 75th percentiles.

4. Discussion

4.1. Integrating local knowledge predictors in seasonal climate forecasts at scale

The approach taken to eliciting and utilising local knowledge in seasonal climate forecasts, presented here is replicable to other contexts. The local knowledge found in this study and the relationship between the predictors and predictands (Sections 3.1 and 3.3.1) is in line with those found in other studies. Waiswa et al. (2007) show a strong relationship could be found for a temperature indicator derived from local knowledge and the onset of the first rains. In addition, Gbangou et al. (2021) find that wind-related indicators are also used for forecasting rain.

Local knowledge predictors (wind direction, speed and temperature) have been analysed separately in this study. However, farmers descriptions of 'cold Mwera winds', for example, implies a combined interpretation of both wind speed, direction and temperature. Exploring those combined indicators – or other ecological or celestial indicators of drought used by farmers (e.g. Chisadza et al., 2015; Gbangou et al. 2021) may be of particular value in some contexts.

Across the geographic contexts covered in this study, we find a stronger correlation between the *number of dry spells* and *timing of onset*

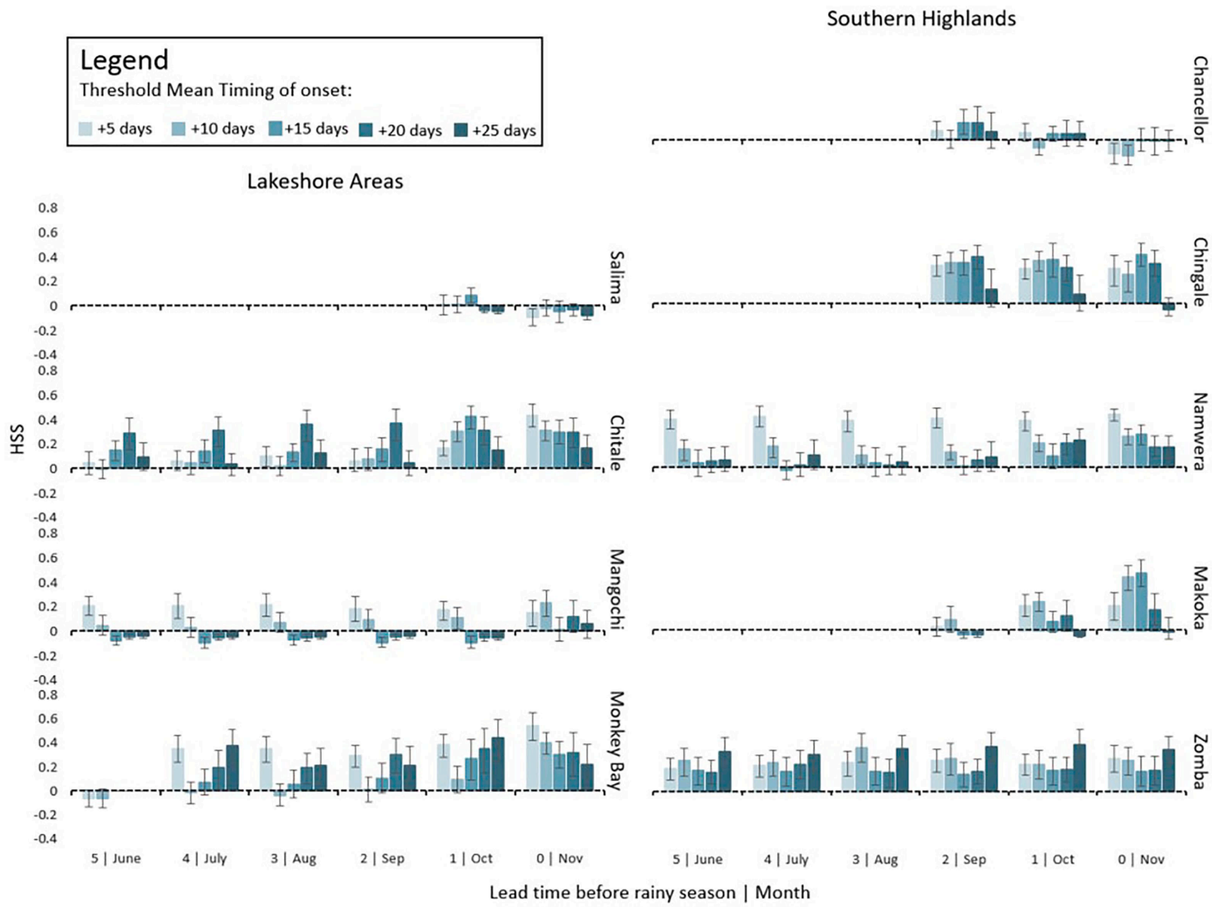

Fig. 6. Heidke Skill Score (HSS) of k-fold cross validation results for stations in Lakeshore Areas (left) and Southern Highlands (right), at different thresholds for a late onset (median +x days). The error bars indicate the 5th and 95th percentiles of the HSS. Skilful forecasts are observed when the HSS is above zero, including the error bar.

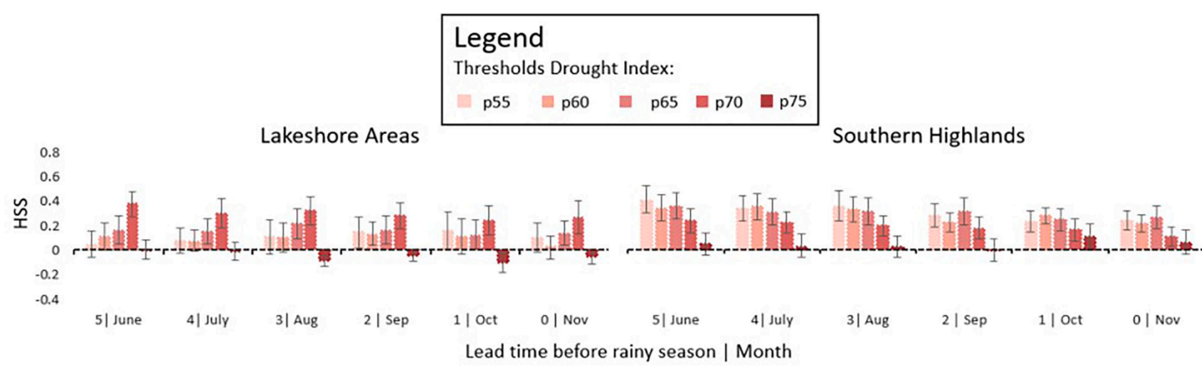

Fig. 7. Heidke Skill Score (HSS) of k-fold cross validation results for Lakeshore Areas (left) and Southern Highlands (right), at different thresholds (55th, 60th, 65th, 70th and 75th percentiles) for the drought index at climate zone scale. The error bars indicate the 5th and 95th percentiles of the HSS. Skilful forecasts are observed when the HSS is above zero, including the error bar.

predictands in the Southern Highlands than in Lakeshore Areas. This spatial variation could be explained by geographic features that could influence meteorological processes. The prevailing wind in Malawi is easterly (from the Indian Ocean). As the name suggests, the Lakeshore Areas climate zone is adjacent to Lake Malawi. The lake may well influence the atmospheric conditions and influence the wind conditions in these areas. Other conditions such as differences in altitude of the stations, the quality of the observation data and limited occurance drought therein may also have influenced the performance.

4.2. Performance of local knowledge indicators

Comparing the local knowledge indicators with the ENSO indicator (ONI) in the correlation analysis (Section 3.2.1), revealed that the local knowledge indicators are more significantly correlated with the locally relevant onset and dry spells predictands than the ENSO indicator. In addition, current seasonal forecasts mostly rely on large processes in the atmosphere and oceans like the ENSO. This study, however, focuses on station or climate zone level and tries to focus on local processes relevant for farmers. The results suggest that the ENSO phenomenon has a predictive value for predicting drought on larger scales (drought index), but limited value for more local, small scale processes such as the onset of rain or dry spells. It is therefore argued that the use of wind and temperature related indicators, and not just ENSO, should be further investigated when (seasonally) forecasting locally relevant variables of dry conditions. Gbangou et al. 2021 also show that forecasts based on local knowledge have higher skill than the forecast of the National meteorological office in Ghana.

The question remains what level of skill is good enough to inform decision-making of farmers. Ziervogel et al. (2005) suggest that if forecasts are not correct 60–70% of the time, then they are unlikely to benefit farmers and may do more harm than good. It remains up to the farmers whether they are willing to adapt their decision making, accept wrong forecasts and lose the (time or financial) investments made. For this to happen, they should be well informed about the forecast skill, and the potential risk of acting on a forecast should be communicated and, if possible, mitigated (Budimir et al., 2020). This should be carefully considered and communicated by stakeholders providing forecast information as part of climate services.

4.3. Local knowledge in climate services context

This paper has focused on one aspect of the wider efforts of co-production of climate services. The local knowledge indicators have not solely been grounded in the design of a forecast but also triangulated and validated by using them as a basis for examining forecast model skill. This is an important element of the co-production of climate services, especially seen through the lens of empowerment (Bremer and Meisch, 2017). However, there is further scope for iteration of local knowledge and forecast models and for these to work together more closely (e.g. to shape what meteorological data is collected, how forecast models are designed, how forecasts are communicated, etc.).

Farmer decision-making is dynamic, multidimensional and contextual; there is a large range of interacting factors that play a role in the decision-making at a particular point in time (Hermans et al., 2021). Calvel et al. (2020) illustrate that the current provision of SCFs in Central Malawi could be improved and better tailored to the farmers. This means that the end-user and their needs should be better understood such that their needs are built into the design and dissemination of the SCFs (Mittal et al., 2021). Tailoring the content of SCFs to the local knowledge of farmers could enhance trust and uptake of information by farmers (Alessa et al., 2008; Kniveton et al., 2015). Bringing together local knowledge in the co-production of seasonal climate forecasts could be an effective way to achieve this (Kalanda-Joshua et al., 2011). Taking farmers' own expectations about the upcoming rainy season into account is therefore very important when communicating a forecast, particularly when they contradict local expectations (Nkomwa et al.,2014).

In some areas of climate services, there is a potential in bringing together and accessing the skill of different predictors for different purposes. For the agricultural sector, the onset of rains and dry spells are important predictands, and local knowledge-based indicators could enhance these forecasts. In addition, it might be worthwhile exploring ways in ongoing efforts on drought forecasting to include local knowledge predictors. Examples of efforts include anticipatory forecast models and phased approaches in early action protocols for humanitarian agencies (e.g. TAMSAT Alert (Boult et al., 2020)). In these applications, wind and temperature predictors could be monitored in real-time to forecast dry conditions in the upcoming rainy season.

Plotz et al. (2017) argue that the value of local knowledge for forecast methods is eroded by the increased investment in conventional climate science approaches and the increased variability and unpredictability caused by climate change. External stakeholders in Malawi perceive the lack of evidence that local knowledge works as its major limitation (Trogrlić et al., 2021). This study, however, found that with a recent dataset (Table 1), indicators may have a predictive value. These findings suggest that meteorological indicators based on local knowledge are not decreasing in its reliability. On the contrary, it could even create opportunities in a changing and more unpredictable environment.

5. Conclusion

Our research integrated local knowledge of smallholder farmers in central and southern Malawi with the seasonal climate forecast, especially drought forecast. Using local knowledge to inform the choice of indicators in seasonal forecast systems and using local knowledge to validate seasonal forecasts has remained inadequately explored in literature. Our forecasting model is based on meteorological indicators from local knowledge and can complement the ENSO forecast variable from the DCCMS. A threshold model was established that relates annually monitored meteorological indicators based on wind direction and wind speed, temperature, and relative humidity and ENSO before the rainy season, to the occurrence of dry conditions during the season. Dry conditions were expressed in variables that farmers require for their agricultural decision-making.

The results show that meteorological indicators informed by local knowledge show a better performance in forecasting the locally relevant dry conditions in comparison to the currently used ENSO-related indicators by the DCCMS. This study, therefore, argues that the local knowledge indicators used in this study can enhance drought forecasting for rainfed agriculture. The inclusion of local knowledge creates opportunities, both in terms of communication and the production of SCFs by national meteorological services. In addition, providing information that is informed by local knowledge can potentially improve the contextual relevance of forecast information for farmers.

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CRediT authorship contribution statement

Ileen N. Streefkerk: Conceptualization, Methodology, Software, Writing – original draft, Visualization. **Marc J.C. van den Homberg:** Conceptualization, Methodology, Writing – review & editing, Supervision. **Stephen Whitfield:** Writing – review & editing, Funding acquisition. **Neha Mittal:** Methodology, Writing – review & editing. **Edward Pope:** Validation, Writing – review & editing. **Micha Werner:** Conceptualization, Methodology, Writing – review & editing, Supervision. **Hessel C. Winsemius:** Conceptualization, Methodology, Writing – review & editing, Supervision. **Tina Comes:** Conceptualization, Writing – review & editing, Supervision. **Maurits W. Ertsen:** Conceptualization, Supervision.

Declaration of Competing Interest

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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cliser.2021.100268.

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