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Review

Local rainfall forecast knowledge across the globe used for agricultural decision-making

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ABSTRACT

The agriculture sector is vital to the world's economy and weather and climate are key drivers that affect the productivity and profitability of agricultural systems. At the same time, weather-related risks pose significant challenges to farmers' livelihoods. Although scientific weather forecast (SFK) is available, many farmers, especially in the Global South, have limited access to this information, and they rely on local forecast knowledge (LFK) to make farming decisions. Many studies also recognize the value of combining both forecasting systems; yet, unlike SFK which is readily available, indicators for LFK needs to be collected first. Therefore, this study identifies and documents the spatial distribution of LFK use for agriculture across the globe through a systematic literature review. Results show that a high number of LFK regions with a total of around 1350 local environmental indicators were found in Africa and Asia and less in South and North America. The low usability of scientific weather forecasts is perceived as the main reason farmers use LFK instead of SFK, yet the accessibility of LFK both for scientists and users, needs to be improved. Indicators based on animals and meteorology appeared to be more frequently used for weather predictions than plant- and astronomy-based indicators. Digitalizing the LFK inventory and collecting more detailed information about the regions where LFK was identified could promote and foster research on integrating scientific and local forecasting systems. This study will draw attention to the importance of LFK in weather forecasting, maintain this knowledge and enhance it.

1. Introduction

The importance of weather and seasonal climate forecasting in the agricultural sector has been increasing rapidly, as the availability of forecast information assists farmers in making informed operational decisions at the farm level. Decisions such as pesticide application, fertilizer type, plant selection, sowing calendar and irrigation planning strongly depend on the provisioned weather forecast or the seasonal weather prediction (Gbangou et al., 2019; Kumar et al., 2020b). Weather- and climate-smart agricultural decision-making leads to improved social, economic, and environmental outcomes by reducing the risks associated with weather-related events, optimizing the use of resources, and increasing the efficiency of agricultural systems (Gbangou et al., 2020; Meza et al., 2008; Paparrizos et al., 2020).

In modern times, it is common for people to rely on scientific information for weather forecasting. Concerning agriculture, while some farmers have access to weather forecast information, this is not the case for all farmers in many parts of the world. Many of them, especially smallholder farmers practicing rainfed agriculture, have limited access, usage, knowledge, and capacity to understand the weather forecast (Ingram et al., 2002).

Smallholders undertake their farm decisions based on indigenous or local practices e.g., using certain local environmental indicators, traditional calendars, and beliefs (Chand et al., 2014; Kumar et al., 2020a). Scientific knowledge is described as modern knowledge that relies on rigorous methods of observations, simulations and data analysis, such as forecasts from large-scale models, station or satellite datasets, etc. Local knowledge is defined as knowledge that is deeply embedded in the local culture and traditions and is linked with long-settled communities and their strong connections to the surrounding environment (Codjoe et al., 2014; Gearheard et al., 2010).

When it comes to weather forecasting for small-scale rainfed agriculture, contextualizing timescale is a paramount aspect that must be considered (Nyadzi et al., 2022). Short-term forecasts are typically most

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relevant for day-to-day activities, and their accuracy has significant implications on the success, or failure, of their crops and livelihoods. Medium-to-long-term forecasts covering timescales of weeks or months are also important for planning purposes, such as deciding which crops to plant in a given season or when to make investments in equipment of infrastructure (Paparrizos et al., 2023).

Advances in weather forecasting have been rapid, based on improved observations and models (Mariotti et al., 2018). Large-scale atmospheric processes are more adequately studied and contribute to enhance predictability (Alvarez-Castro et al., 2018; Faranda et al., 2019). Nevertheless, despite the increase in resolution and complexity of weather forecast systems, the atmosphere's chaotic nature in many cases limits short-term predictability; especially concerning tropical rainfall variability which undergoes pronounced interannual and intra-seasonal fluctuations (Moron and Robertson, 2020). For example, the type of forecasting system used for nowcasting is radically different from that used for seasonal forecasting. Their skill levels are also significantly different, and it can be presumed that the integration of indigenous knowledge in the forecasts might differ as well. Research indicates that smallholder farmers around the globe use both local and/or scientific forecasting knowledge on weather and climate (Gbangou et al., 2021; Kumar et al., 2020b; Orlove et al., 2010). The reasons that smallholder farmers make use of combined weather forecasting are multiple. Firstly, scientific forecast information in many circumstances has limited skills in accurately simulating the prevailing weather conditions at a very local scale (i.e. community scale in the tropics) (Derbile et al., 2016; Paparrizos et al., 2020, 2023). Secondly, farmers have limited ability to understand, accept and eventually use scientific weather forecasts (Gbangou et al., 2020; Ingram et al., 2002). Thirdly, the information that is being provided by scientific sources is not tailored to their context-specific needs (Brasseur and Gallardo, 2016; Hewitt et al., 2017; Kumar et al., 2021; Nyadzi et al., 2019). Moreover, scientists claim that local weather and climate forecast knowledge has decreased its trust due to the loss of indicators as a result of climate change (Balehegn, 2015; Balehegn et al., 2019; Nkomwa et al., 2014; Radeny et al., 2019; Ziervogel and Downing, 2004); or it is subject to scepticism due to replicability issues that limit knowledge spread in practical applications and science (Gilchrist et al., 2005; Huntington, 2000; Pierotti and Wildcat, 2000). Finally, a systematic assessment of this knowledge is still lacking (Lebel, 2013). Integrating both types of forecasting knowledge could improve weather and climate information provision (Gbangou et al., 2021; Luseno et al., 2003; Nyadzi et al., 2018; Nyadzi et al., 2020). But how to integrate two bodies of knowledge emerging from such different world views, with fundamentally different definitions and meanings? A way forward is to utilize local (or indigenous) environmental indicators as a boundary object capable of facilitating effective communication between two distinct knowledge systems (Star and Griesemer, 2016). Many agricultural systems around the world rely on local weather and climate forecast knowledge, utilizing biophysical indicators and considering the environment (e.g., Balehegn et al., 2019; Nyadzi et al., 2021; Reyes-García et al., 2019; Zuma-Netshiukhwi et al., 2013). These indicators can range from biotic (plant phenology and animal behaviour) to atmospheric conditions, and even astronomy is used (Roncoli et al., 2002). A first attempt to document indigenous forecast knowledge indicators was performed by Alves and Barboza (2018) that they documented animals as ethnozooindicators to predict weather and climate. Their results show that human populations worldwide have developed abundant local knowledge for understanding such singularities to better understand the ecology of local animals and to predict natural phenomena.

This paper introduces the concept of 'local environmental indicators' as specific indicators used to forecast atmospheric conditions for farm decision-making. According to Roncoli et al. (2002), farmers integrate various environmental observations with spiritual traditions. Additionally, they combine local environmental indicators with local technology or scientific forecasts (Speranza et al., 2010). The scientific community can relate these observable indicators to their forecasting methodologies. Initial efforts by Gbangou et al. (2021) and Nyadzi et al. (2022) demonstrate that integrated forecast systems, under specific conditions, can outperform both scientific and local forecasting systems, enhancing forecasting skill and usability for farmers in terms of salience, legitimacy and trust. However, Nyadzi et al. (2022) suggest that longer time series from different farming communities are necessary to robustly validate the reliability of the proposed methodologies. Nevertheless, long-term local forecasts datasets are unavailable, while science-based forecasts can generate long-term datasets using hind-cast methods. Therefore, as an initial step towards developing a global database for integrating scientific and local weather forecast knowledge, this study aims to identify and document the spatial distribution of LFK use for agricultural decision-making across the globe. The study addresses two main questions: (1) which local environmental indicators are employed by smallholder farmers for local weather forecasting in different regions globally, and (2) how are these indicators utilized to forecast rainfall for agricultural decision-making.

2. Methodology

2.1. Key terms

In the literature, there is a proliferation of diverse labels and competing definitions assigned to what is commonly referred to as Local Knowledge (LK). These labels include indigenous knowledge (IK), traditional knowledge (TK), traditional ecological knowledge (TEK), ethnoscience, folk knowledge, rural knowledge, and indigenous science. While these terms may have different connotations, they are often used interchangeably throughout the literature. Nonetheless, LK remains the dominant terminology used in the searched literature. It is important to note that Local Knowledge (LK) lacks a single, universally accepted definition across the different strands of literature. The absence of a standardized definition can be attributed to the diverse viewpoints and circumstances under which it is utilized. However, certain elements remain consistent in all available definitions (Nyadzi et al., 2021). Emeagwali and Dei (2014) define local knowledge as accumulated strategies, practices, techniques, tools, intellectual resources, explanations, beliefs, and values in a locality, free from external impositions. TK is often used interchangeably with IK, with TK encompassing broader knowledge and IK focusing on local communities (Brush, 2005). TEK is cumulative knowledge, practice, and beliefs transmitted culturally, relating to relationships among living beings and their environment (Berkes et al., 2000). TEK is a subset of TK and a part of IK, resulting in substantial overlap between these terms. In this paper, the overarching term L(*F*)K will be employed to encompass IK, TK, and TEK. The relationship between these concepts, as defined in literature, is illustrated in Fig. 1. Weather forecasts based on local knowledge (hence, not on scientific knowledge) will be referred to as local forecast knowledge (LFK).

2.2. Data collection and analysis

A systematic literature review was conducted to identify the locations where LFK is employed, and the local environmental indicators utilized to deliver localized weather forecasts for agricultural decision-making. These locations encompass various geographical units such as regions, districts, or provinces within the country.

2.2.1. Systematic literature review (SLR)

The Systematic Literature Review (SLR) conducted in this study comprised of two main parts. Firstly, an extensive search for relevant literature was conducted across various databases. Secondly, a comprehensive literature search was carried out by examining the references of the identified literature. The SLR methodology adopted in this study followed the steps outlined by Kable et al. (2012). The detailed steps are described below and are summarized in Table 1. Annex 1

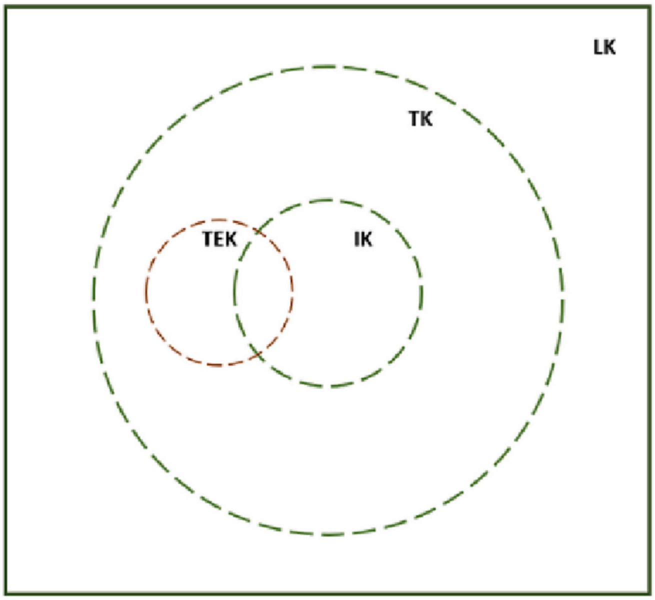

Fig. 1. Local (Forecast) Knowledge serves as an overarching term, encompassing Indigenous Knowledge (IK), Traditional Knowledge (TK), and Traditional Ecological Knowledge (TEK).

Table 1
Summary of systematic literature review steps.

Searching (steps 1–3)	Extended literature search in popular databases, such as Scopus, Web of Science, and Google Scholar (English literature)
Documenting (steps 4–5)	Search strings were used (see Annex 1), and a total of 3945 articles were found (Scopus: 2429 and Web of Science: 1516)
Screening (steps 7–9)	The StArt tool was employed to manage and organize the 3945 articles, remove duplicates and articles where no LFK and indicators on weather and climate forecasting were mentioned, leaving 107 articles.
Critical appraisal (steps 10–15)	107 critical appraisals were conducted by reading the full text to determine if the study addressed LFK and indicator use in agriculture. 59 articles were found to provide useful information and are used in the current study.

presents the search strings and number of articles obtained per database.

- **Searching (steps 1–3):** The objective of this step was to comprehensively gather research articles pertaining to local environmental indicators being used worldwide. To achieve this, an extensive literature search was performed using the Scopus, Web of Science, and Google scholar databases. The search was specifically restricted to English literature, while no limitations were imposed on the publication date, as all literature that could contribute to a comprehensive list of LFK was considered valuable.

- **Documenting (steps 4–5):** In Scopus, three search strings were used, and one was used in Web of Science. In the first screening with Scopus, some keywords such as 'traditional', 'forecast', 'weather', and 'agriculture' were used. Next, we combined keywords such as 'local knowledge', 'traditional knowledge', etc. to further identify literature. The search, however, only resulted a few extra articles. Lastly, we used three main keywords ('forecasting', 'local farmers', and 'weather') to assess whether there is additional literature that fits the search. Since this three step string-search did not yield any further results, we decided to use one search string for the Wed of Science. These search strings were carefully selected to maximize the retrieval of relevant literature. The Scopus search yielded a total of 2429 articles, while the Web of Science search identified 1516 articles. Subsequently, a search was conducted in Google Scholar, following the Scopus and Web of Science searches, but no additional articles beyond those found in Scopus and Web of Science were discovered. In total, across all databases, 3945 articles were found.

- **Screening (steps 7–9):** To manage and organize the 3945 articles, the StArt (State of the Art through Systematic Review) tool was employed. Initially, 267 duplicates were removed, resulting in 3679 articles for further review. The screening process involved assessing the titles, keywords, and abstracts of these articles. Articles without an available abstract or lacking any mention of weather, forecasting, LFK, local environmental indicators, or their synonyms in the title, keywords, or abstract were excluded. Synonyms for these terms had been identified in advance. Following the initial screening, 107 articles remained, which were deemed relevant based on the research questions. The reference lists of these 107 articles were examined using the backward snowball effect but all the mentioned articles had already been identified in the previous steps.

- **Critical appraisal (steps 10–15):** Out of the 107 relevant articles, two duplicates were identified and removed, resulting in a final set of 105 articles. These articles underwent a critical study appraisal to determine their focus on LFK for agricultural decision-making. Articles that utilized LFK for purposes other than agricultural decision making, were excluded. Ultimately, 59 articles were deemed useful and are therefore used for the study.

2.2.2. Data extraction and analysis

The 59 scientific literature articles that were identified, were analysed with the purpose to extract information and gain an overview of the geographical distribution of LFK implementation. Furthermore, all the indicators mentioned in each location were identified and categorized. The extracted indicators were then classified into five categories: plants, animals, meteorological phenomena, astronomical phenomena, and indicators that did not fit into these categories (referred to as "others"). It is worth mentioning that our categorization of indicators differs from Reyes-García et al. (2019), who classified indicators based on climatic, physical system, biological, and human factors. In their study, they compiled the indicators to indicate climate change impacts while we focused on compiling indicators specifically used in agricultural decision-making. Supplementary Tables A–E provide a full list of the local indicators identified through the literature review. Additionally, within the categories of animals, meteorology, and astronomy, further subcategories were created to offer a comprehensive overview of the types of indicators identified. Alongside the indicators themselves, relevant information such as indicator signals, predictions, and periods of indicator observations were extracted from the literature.

3. Results

3.1. Locations where LFK is used for farm decision-making

The results of the SLR provide an overview of the locations where LFK indicators are used for agricultural decision-making, as depicted in Fig. 2. The red dots on the map represent approximate locations where previous research was conducted, as the exact coordinates were not always provided in the studies. A total of 65 locations/regions were identified where farmers use local indicators for weather and climate forecasting. Four locations are found in North America, five locations are in South America, 13 locations are in Asia, and 48 locations are found in Africa. Most of the locations are concentrated in the global South, particularly in Africa and Asia. Within Asia, 9 out of the 13 locations are found in India. In Africa, 18 locations are found in South Africa and East Africa, and 12 regions are identified in West Africa. Some studies researched multiple locations, while others focused specifically on one particular geographical location. For a detailed literature overview presenting these locations, the reader is referred to Annex 2 that provides a comprehensive summary of the studies conducted in each location, shedding light on the utilization of LFK and its associated indicators.

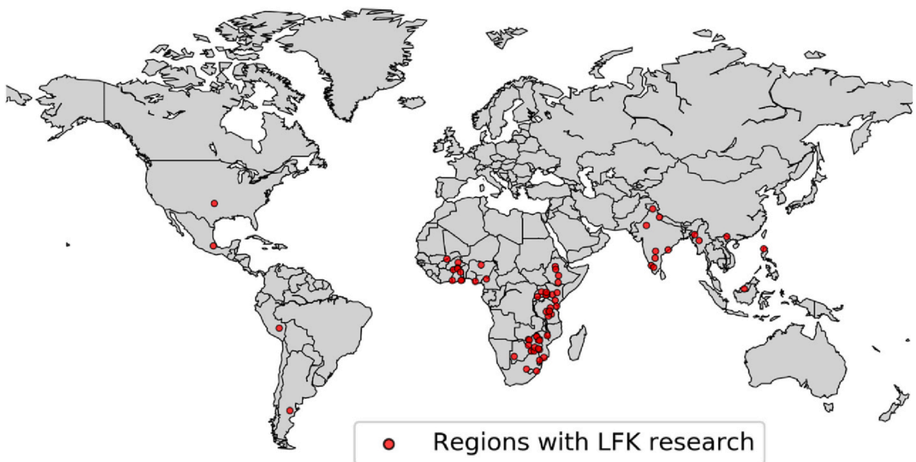

Fig. 2. Locations around the world utilizing Local Forecast Knowledge (LFK) indicators in agricultural decision-making for weather and climate forecasting. The red dots represent approximate locations where previous research has been conducted. The map showcases various regions in North America, South America, Asia, and Africa where LFK indicators are utilized, with a notable concentration in Africa and Asia.

3.2. LFK indicators and their use in weather prediction

Table 2 provides an overview of the number of indicators per category and continent. In our study, a total of 1349 LFK indicators used for agricultural decision-making were extracted up until the date of data collection. However, it is important to note that this number does not represent 1349 unique indicators. Instead, it includes the same indicator with different signals and predictions. For instance, considering the example of frogs as a local indicator used in India to indicate rain, in Rajasthan, India, 'frogs start to make a lot of noise' indicates near rainfall onset (Pareek and Trivedi, 2011; Sarkar et al., 2015). In Uttarakhand, India, however, croaking of frogs in the afternoon indicates imminent rain (Rautela and Karki, 2015). Here, although 'a lot of noise' and 'croaking' might appear as the same indicator and presumably the former description also falls under the definition of croaking, the citing literature uses different terms. Hence, we counted the frog indicator two times. Regarding animal indicators in Asia, out of 140 indicators found, approximately 66 different types of animals are used as indicators. However, determining the exact number of unique animal indicators remains challenging due to variations in terminology within the literature. Some sources use general terms like 'worm', while others provide more specific names such as 'Earthworm' or 'Mopane worm'.

Most of the indicators were found in Africa (984), followed by Asia (314), and North America (43). The fewest indicators were found in South America (8). In Africa, LFK indicators are well implemented in 15 countries, such as Botswana, Burkina Faso, Cameroon, Ethiopia, Ghana, Kenya, Malawi, Mali, Mozambique, Nigeria, South Africa, Tanzania, Uganda, Zambia, and Zimbabwe. Around five countries in Asia use LFK to forecast weather. These countries are India, Malaysia, Myanmar, the Philippines, and Vietnam. In North and South America, farmers in Mexico, the US, Argentina, Peru, and Bolivia also use the LFK to predict the weather. The majority of indicators (38 %) fall under the animal category, where farmers observe animal behaviour, sounds, or movement. Meteorological indicators make up a significant portion (30 %), including wind direction, rain duration, and cloud movement. Plant-based indicators account for 17 % and involve tracking flowering and fruiting patterns. Astronomical indicators have a smaller share (12 %), such as the presence of a halo around the moon or the appearance of some stars. The 'other' category includes indicators that are not classified under animal, meteorological, plant, or astronomical categories. An example of such indicators is the association between the gender of newly born babies in Zimbabwe.

Fig. 3 presents the distribution of LFK indicators per category for meteorology, animals and astronomy, while Fig. 4 shows the global spread of indicators for LFK locations. The most commonly used meteorological indicators worldwide for weather prediction for rainfed agriculture are wind (113 indicators), clouds (72 indicators), and temperature (55 indicators). Across the world, there were found 189 bird indicators, 150 insect indicators, 77 mammal indicators, and 44 amphibian indicators, all belonging in the animal category. In the astronomy category, the moon (86 indicators), star (48 indicators), and sun (19 indicators) were the most used indicators based on literature. Analysing the categories, animal indicators are mostly used in India, Ghana, and Zimbabwe. (dark reddish colour in Fig. 4). In India and Zimbabwe, local indicators based on meteorology have the highest usage compared to other locations (red colour). Zimbabwe has the highest number of astronomical indicators (orange colour). Regarding plant indicators, Zimbabwe and Tanzania are the countries that make the most use of them.

Next, we separated the indicators that can be used to forecast the weather based on their lead times. Generally, 55 % of indicators are utilized for short-term forecasting with a maximum lead time of 7-days (Gyampoh et al., 2011; Jiri et al., 2015; Tolo et al., 2014), while 45 % are employed for longer forecasting lead times, such as bi-weekly, monthly, and seasonal forecasts (Rivero-Romero et al., 2016; Son et al., 2019). It was challenging to determine precise lead times for some indicators, as

Table 2
Overview of the LFK indicators found per continent and category.

	Animals	Meteorological indicators	Indicators based on plants	Astronomic indicators	Other indicators	Total LFK indicators per continent
N. America	22	5	13	3	0	43
S. America	6	0	0	2	0	8
Asia	140	99	43	21	11	314
Africa	340	306	168	136	34	984
Total LFK indicators per category	508	410	224	162	45	1349

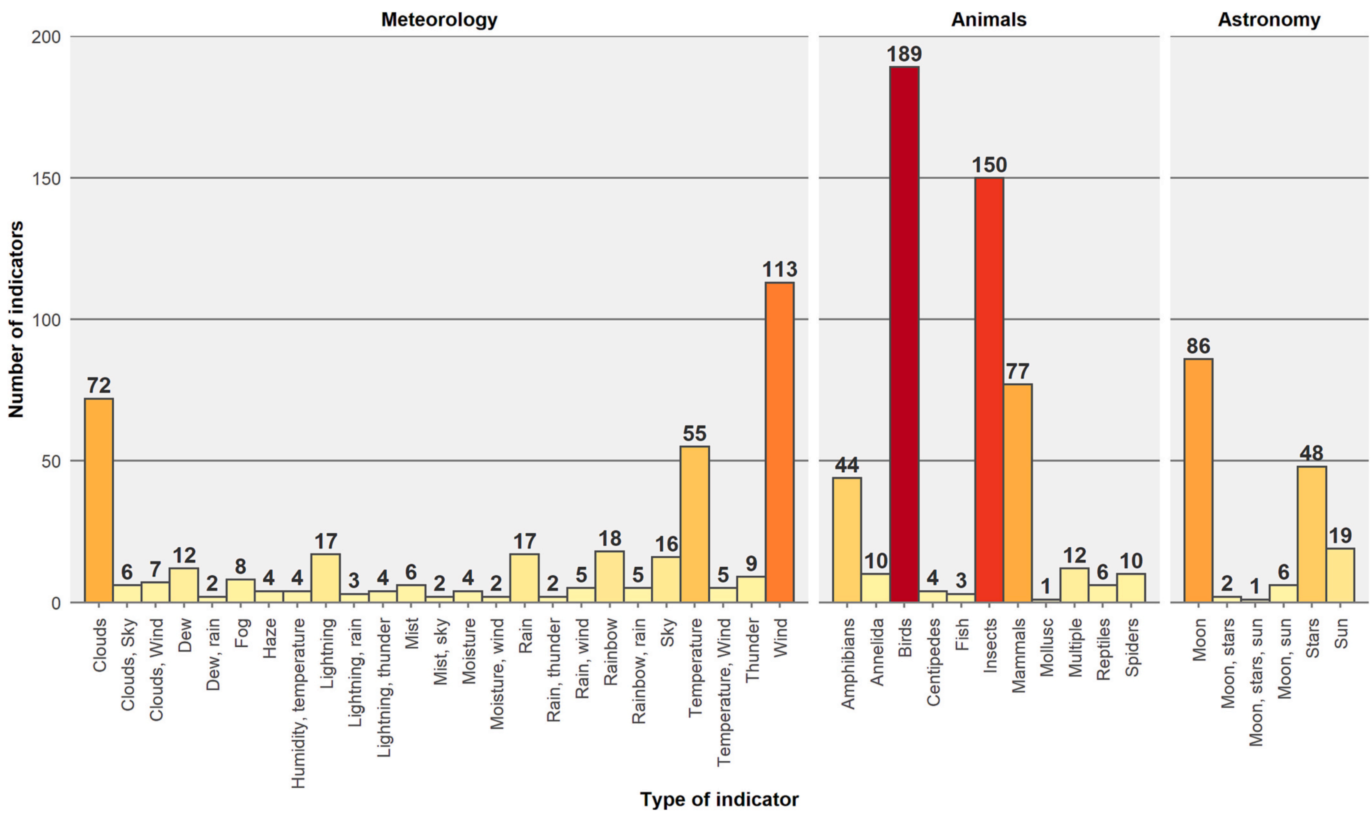

Fig. 3. Total number of LFK indicators for category meteorology, animals, and astronomy.

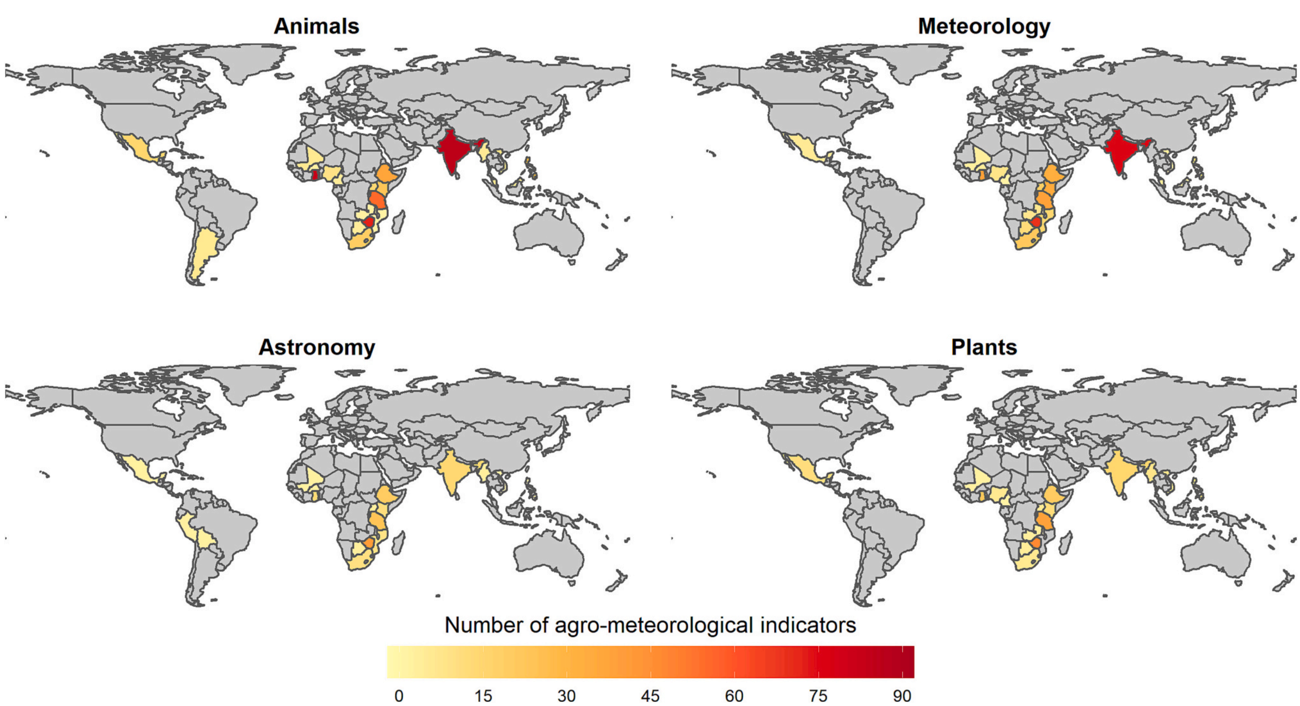

Fig. 4. Number of LFK indicators per category and location.

many scholars did not provide detailed information. For example, authors might mention that rainfall onset is approaching without specifying a specific timeframe, such as three days, or a week. Therefore, we made subjective judgements based on our own expertise and experience to group the indicators into short and long lead forecasting times. Our analysis revealed that animal indicators and meteorological indicators are primarily employed for short-term weather forecasting for rainfed agriculture. On the other hand, plant and astronomy indicators are predominantly used for weather events expected to occur beyond a week. The number of meteorological indicators used for short-term forecasting is more than double that of long-term forecasting. Farmers commonly rely on seasonal LFK to predict weather and climate events such as drought, variations in rainfall during the rainy season, and the duration of the rainy season. An additional classification of the LFK indicators according to the conditions that these indicate (wet or dry conditions), is presented in Fig. 5. According to the results, most of the LFK indicators (72–86 %), indicate wet conditions, while 13–25 % indicate dry conditions. Some indicators are used to predict both wet and/or dry conditions respectively, and are classified separately.

3.3. Categories of LFK indicators

3.3.1. Animal indicators

Among animal-based indicators, the animal category is further divided into vertebrates, including amphibians, birds, mammals, reptiles, and fish, and invertebrates, such as centipedes, insects, spiders, annelids, and molluscs. The sub-category of bird indicators is the most commonly used for agricultural decision-making in rainfed agriculture (Fig. 4). Some scholars mention combinations of multiple animals, like birds and insects. The use of bird species as LFK indicators exhibits a great variety. Ducks, storks, and swallows are examples of species utilized in multiple regions. In some cases, no specific descriptions of bird species were provided, and the general term "birds" was used instead. Different regions employ different bird species to predict the occurrence of rain. Another less common observation involves the orientation of birds' nests. Insects, as a group, also provide a substantial number of indicators based on animals. This sub-category includes ants, termites, dragonflies, and butterflies. Ant appearances are among the most frequently used observations to predict rainfall. Termites are primarily employed to forecast wet and dry conditions. Dragonflies, on the other hand, are observed based on their movement and flying patterns. Regarding mammals as LFK indicators, a wide range of species is used, particularly in Africa but also in Asia, North and South America, to predict the weather. In the amphibian category, frogs and toads are primarily used, along with the occasional reference to gecko singing. Of the 42 frog-based indicators, 41 rely on the croaking of frogs. The croaking serves as an indicator of expected rain or the onset of the rainy season, but it does not predict droughts. Most of these indicators are used during spring or summer, although some are applicable throughout all seasons – as demonstrated in the case of Rautela and Karki (2015) for Uttarakhand (India).

3.3.2. Meteorological indicators

The meteorological indicators encompass various subcategories (Fig. 4) due to the utilization of multiple meteorological elements in a significant number of indicators. Each element has its own subcategory, resulting in a total of 36 subcategories. Among these indicators, the majority is based on wind observations, followed by clouds, temperature, rainbows, rain, lightning, and sky observation. Annex 3 provides further elaboration on the three main LFK meteorological indicators used by farmers for weather forecasting for rainfed agriculture: wind, clouds, and temperature. Wind observations used for weather forecasting are primarily documented in Asia and Africa, focusing on the direction, strength, and the occurrence of whirlwinds (Chang'a et al., 2010). Cloud observations encompass various factors such as the number of clouds, their colour, shape, direction, and speed. Farmers often consider multiple cloud observations in their decision-making process, such as the combinations of cloud colour and shape. Common colours used for cloud observations include black (also referred to as dark), white, and red. Instances where colour-based observations of clouds are used are found in Uganda, Cameroon, and Ghana. Temperature observations play a crucial role in weather prediction and are widely used by many farmers. For example, farmers may assess night temperatures to anticipate the weather for the following day. In some regions, weather prediction is based on long-term temperature observations, spanning yearly, seasonal, and monthly periods. Elsewhere, farmers rely on morning temperatures to gauge the expected weather for the day. Extreme temperature observations are also used by multiple groups.

3.3.3. Astronomical indicators

The halo around the moon serves as an indicator in various regions of Africa. It is observed in the northern Region of Ghana and Greater Accra (Gyampoh et al., 2011), the Central District of Botswana (Mogotsi et al., 2011), Makueni County in Kenya (Speranza et al., 2010), Free State and Mpumalanga in South Africa (Ubisi et al., 2020; Zuma-Netshiukhwi et al., 2013), and the Tanga and Dodoma Regions of Tanzania (Elia et al., 2014; Mahoo et al., 2015). In Zimbabwe, it is utilized in the Mashonaland Central and East, Masvingo, Midlands, and the Mzingwane catchment area (Chisadza et al., 2013; Gwenzi et al., 2016; Jiri et al., 2015; Shoko and Shoko, 2013; Tanyanyiwa, 2018). The colour of the moon is another indicator used by local communities. Observing also plays an important role in weather prediction, with various factors considered. These include the presence of multiple stars, star size, constellations, and star brightness. In Botswana, Mogotsi et al. (2011) mention that the appearance of a large star is associated with the prediction of rain in the Central District and Kgalagadi North District. Farmers in different regions often rely on star appearance and constellations as LFK indicators to forecast weather. For instance, Andean farmers in South America use a star constellation called Taurus, as explained by Orlove et al. (2010). A year characterized by bright and large stars in Taurus cluster indicates the expectation of abundant rainfall. In contrast, when the stars appear dim or small, rain is anticipated to arrive late and scarce. Similar to moon observations, the presence of a halo around the sun is commonly used in Africa and Asia, compared to other indicators.

3.3.4. Plant indicators

Farmers around the world use plant indicators in various ways, employing multiple plants to predict specific weather events or relying on a single plant to forecast multiple weather phenomena. During the data mining process, plant indicators were primarily identified in Africa, Asia, and North America (Fig. 4). The majority of the plant names are provided in English or scientific terms often using Latin nomenclature. However, in Africa, many plants are described by their local names, posing a challenge when comparing results across different regions. A significant number of indicators using plants are based on the observation of flowers. Farmers primarily consider the timing of flowering (early, normal, or late), the quantity of flowers, and the appearance of flowering as key observations used to establish LFK indicators. Plant-based indicators are predominantly utilized for monthly and seasonal predictions. For instance, in Cameroon, the blooming of Scadaxus Multifluros in late February to early March indicates that the onset of the rainy season is expected within three weeks to one month (Tume et al., 2019). Another example is observed in the sprouting of leaves on the Minusi Mikwee tree, which signals the approaching rainy season (Kijazi et al., 2013). These plant indicators serve as valuable cues for farmers to anticipate and prepare for changes in weather conditions.

3.3.5. Other indicators

In addition to the previously mentioned categories and indicators, there are several indicators used by farmers for making farm decisions that do not fall under any of the aforementioned categories and are classified as 'Other'. In Supplementary Table E, a total of 45 indicators are listed under the "Other" category, with 34 originating from Africa and 11 from Asia. Among the most intriguing indicators in this category are those related to animal intestines, which are specific to Kenya and Ethiopia. These indicators include observations such as the colour of the intestine and the amount of food present there, childbirths, body sweats, pain in body joints or sores, soil conditions, and more. Annex 3 provides a comprehensive overview of this category, along with detailed descriptions of their significance in local weather forecasting.

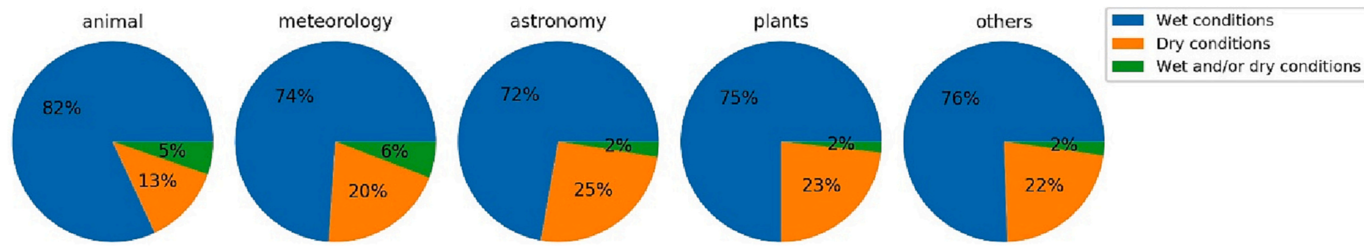

Fig. 5. Classification of LFK indicators based on what they predict (wet, dry, or both conditions).

4. Discussion

This study aimed to identify local environmental indicators and examine their use in forecasting rainfall worldwide. Its primary objective is to initiate a global discussion on the significance of local environmental indicators in weather prediction for agricultural decision making.

4.1. Use of LFK indicators and implications for agricultural decision-making

Based on the finding of the Systematic Literature Review, it is evident that scientific weather forecasts are often perceived as lacking location-specific information or not adequately downscaled for local farmers. In several African countries, literature suggests that farmers consider the timing of the scientific forecasts to be unreliable, and the process of obtaining scientific forecast information is often challenging and not user-friendly (Balehegn et al., 2019; Mahoo et al., 2015; Roncoli et al., 2002). Similarly, in Pacific countries, limited access to scientific weather forecasts has been identified as the primary reason for farmers relying on local forecast knowledge (L. Chambers et al., 2019).

The lack of availability of scientific weather forecasts is also observed in the Andes, as described in Orlove et al. (2010). Farmers in this region face rugged farming conditions and have limited resources to support their agricultural activities. To overcome these challenges, they rely on simple astronomical observations to predict rainfall. In the El Carmen region of Mexico, the high usage of LFK is attributed to a lack of education, particularly among the older generations who depend heavily on seasonal agriculture (Rivero-Romero et al., 2016). Success in their agricultural activities is closely tied to local indicators. Conversely, the younger generation is increasingly moving away from rural areas in pursuit of better education and employment opportunities.

In Sarawak, East Malaysia, the Badeng people rely on traditional environmental sensations and their own intuition instead of scientific forecasting systems. Despite the presence of a nearby weather station, the collected weather data is not accessible to the public, including the Badeng people (Garay-Barayazarra and Puri, 2011). In the dry zone of Myanmar, limited access to technological support poses challenges for farmers in adapting to climate change (Swe et al., 2015). Although new techniques are available, they remain inaccessible to farmers, who continue to rely on their conventional practices and LFK for weather prediction (Swe et al., 2015). Traditional knowledge also plays a significant role in planning farming activities in Ilocos Norte Province of the Philippines. Farmers use LFK to predict the start of the rainy season and the seasonal outlook, which helps them schedule appropriate farming activities, such as selecting cropping patterns and determining cropping intensity. While some locals are embracing technology, many traditional farmers still consider their LFK systems to be more accurate and reliable (Mahoo et al., 2015). Furthermore, local knowledge is characterized as dynamic, evolving through time, social interactions, experiments, and transmission (Brondízio et al., 2021). The Philippine Atmospheric, Geophysical, and Astronomical Services Administration (PAGASA) recognizes and acknowledges these LFK systems (Galacgac and Balisacan, 2009). In the Alves and Barboza (2018) study, 201 animal species were identified that are used as weather and climate indicators, with birds being the most commonly used, followed by insects and mammals, which aligns with the findings of the current study.

The number of studies conducted on LFK varies across continents, with Africa exhibiting a higher number compared toother regions. This disparity can be attributed to several factors. Primarily, a significant proportion of African farmers engage in rainfed agriculture and rely heavily on rainfall for their farming activities (Wani et al., 2009). The limited distribution of meteorological stations in Africa, coupled with the inherent inaccuracies in forecasts provided by national met-offices, further emphasizes the need for alternative weather prediction methods (Nyadzi et al., 2019). Additionally, the prevalence of LFK practices in Africa can be attributed to the vulnerability of farmers in the region, their limited access to available technology and information, and their reliance on traditional agricultural practices (Mahoo et al., 2015). These factors contribute to the significance and prominence of LFK in agricultural decision-making in Africa. In contrast, no specific regions in Europe were identified where LFK is used for agricultural decision-making. This disparity may be due to the widespread adoption of information and communication technology, along with improved weather forecasting capabilities, which prompt European farmers to rely solely on scientific information (Soares et al., 2018). It is also possible that insufficient research has been conducted on LFK identification and its relevance and added value in Europe, or the existing knowledge may not be well-documented. Furthermore, the availability of agricultural infrastructure such as reservoirs, irrigation canals, and pumps in Europe may provide farmers with alternative means of managing water resources, reducing their dependence on LFK. This differs from many countries in Africa and Asia, where rainfed agricultural systems are more prevalent (Wani et al., 2009). Finally, when considering the LFK indicators, it is important to differentiate between indigenous knowledge that relies on potentially valuable observations (such as animal or plant behaviour, meteorological phenomena), even in the absence of specific scientific evidence, and indigenous knowledge that is deeply rooted in a community but unlikely to enhance numerical forecasts (for instance, weather prediction based on the gender of new-born babies). Certain indigenous knowledge holds greater potential for integration into "scientific" forecasts compared to others.

4.2. Towards documentation and preservation of LFK

Interest in local knowledge for weather and climate prediction is increasing, and the lack of long-term time series data on LFK poses a challenge. Consequently, there is an emerging need to develop suitable databases for storing and managing the collected information. Chambers et al. (2017), suggest four basic principles for an appropriate LFK database: (1) preservation of knowledge and cultural context, (2) consideration of intellectual property, ethics, and cultural sensitivities regarding data sharing and use, (3) robust system design accounting for costs, maintenance, and connectivity (e.g. internet access), and (4) ensuring sustainable, continuous use and growth of LFK and system. To bridge this critical gap and preserve and enhance the importance and visibility of local weather forecast knowledge, a digital inventory in the form of an interactive StoryMap has been developed using ArcGIS online. This StoryMap provides an interactive and visual representation of the data collected in the current study, specifically highlighting the elements of Annex 2. The StoryMap can be found here.[1]

4.3. Caveats in identifying the LFK locations and local indicators

During the SLR, only English literature was assessed, resulting in the exclusion of research written in local languages. This limitation means that a significant amount of research contacted in South America, which is written in languages other than English, was not included (Amano et al., 2016). Similar limitations apply to West Africa and Francophone countries. LFK indicators documented in languages other than English were not captured due to language barriers and limitations. Additionally, a criterion during the SLR was that the indicators must be related to agriculture. Therefore, indicators used for other purposes, such as conservation, and sustainable ecosystem research for identifying climate change impacts, were excluded (Lam et al., 2020; Reyes-García et al., 2019; Tengö et al., 2021; Tengö et al., 2014). The use of LFK for agricultural decision-making and other activities may not always be clearly delineated, introducing some uncertainties. The decision to only include English literature and focus on indicators related to agriculture implies that more articles and regions with LFK could have been identified. However, the study's scope specifically targeted the documentation of LFK indicators related to agricultural decision-making.

At the beginning of this study, it was challenging to anticipate the types of indicators that would be identified. During the preliminary research, indicators related to animals and plants were frequently encountered, along with some meteorological indicators. However, there was limited research on astronomic indicators. This disparity in the number of indicators in the astronomy category may be attributed to the use of traditional calendars. Certain indigenous communities such as the Aborigines in Australia, still rely on traditional calendars, which often incorporate astronomy for weather prediction (Hamacher et al., 2019). Hence, these articles were excluded from the study. Future research could explore the inclusion of traditional calendars as an astronomic indicator for weather forecasting.

Categorizing the indicators into specific categories and subcategories sometimes posed challenges, especially when indicators had elements that fell into both astronomy and meteorology (e.g. the combination of moon and clouds). To address this issue, it was determined that the most influential element for weather prediction would govern the category in which the indicator would be placed.

4.4. Rationale for future studies

The comprehensive assessment of the literature highlights the concerns raised by Balehegn et al. (2019) regarding the disappearance of LFK and the increasing difficulty faced by local farmers in weather prediction. Anticipated changes in observed indicators are expected in the future, primarily as a result of climate change. Indicators predominantly based on animals and plants will be affected. For instance, the migration patterns of many animals are likely to shift due to changing climate conditions, and the flowering behaviour of plants may also change, occurring earlier or later than usual (Cohen et al., 2018). Despite being aware of these changes, farmers who reply on these indicators continue to use them for weather predictions. However, these changes also provide opportunities to study, interpret and utilize new indicators. For example, the migration of bird presents an opportunity to incorporate this indicator for weather prediction in specific regions. Documenting such developments in future studies is essential.

An interesting finding regarding the indicators is the occurrence of the same indicators (mostly animals) being used in multiple locations, but with different signals and predictions. These findings emphasize the importance of collecting LFK specific to each study location, as the development of a skilful local forecasting system is location-specific, especially in regions where reliable scientific weather information is limited.

A few studies have evaluated the performance of LFK and SFK in the same location and time periods. Gbangou et al. (2021) concluded that the SFK yields higher forecast skill than LFK in the greater Accra region of Ghana. However, when three or more local indicators are observed, the skill of LFK becomes equal to or even higher than SFK, indicating that the more the indicators are observed, the better the prediction. In a different region of Ghana, Nyadzi et al. (2022) found that overall, LFK outperforms SFK, particularly in predicting above-normal precipitation events in the northern region. The complexity of determining which forecast is more skilful and reliable has led farmers in some regions to use both forecasts, resulting in efforts to combine LFK and SFK (Balehegn et al., 2019; Kalanda-Joshua et al., 2011; Mahoo et al., 2015; Roncoli et al., 2002). The integration of these two knowledge systems may offer skilful forecasts (Nyadzi et al., 2022) and alleviate the challenge of choosing between LFK or SFK. Several studies indicate that many farmers prefer an integrated forecast over selecting a single forecast (Kalanda-Joshua et al., 2011; Paparrizos et al., 2023). Thus, promoting the integration of SFK and LFK to develop skilful forecasts is recommended.

5. Conclusions

This study represents the first comprehensive effort to document Local Forecast Knowledge (LFK) and the specific locations where LFK and local environmental indicators are utilized by smallholder farmers in their agricultural decision-making processes, alongside scientific weather forecasts. Through a rigorous systematic literature review (SLR), the present study identified the regions where LFK is employed and the diverse range of LFK indicators utilized by farmers. LFK is characterized for its locality-specific nature, offering distinct advantages for local farmers compared to SFK. The limited accessibility of scientific forecasts is a key driver for smallholder farmers worldwide to rely on LFK instead. Our findings indicate that LFK is predominantly utilized in Africa and Asia, with lesser instances in North and South America. This study has documented approximately 1350 local environmental indicators employed by smallholder farmers globally to predict weather patterns for their farm activities. Among these indicators, animal-based and meteorological indicators are the most prevalent for daily, monthly, and seasonal weather prediction, followed by plant-based and astronomical indicators. By compiling an LFK digital inventory from the extensive literature and gathering more detailed information about the identified LFK regions, we can advance research in several crucial areas. This includes the identification of additional LFK regions yet to be explored, the integration of forecasting systems by combining LFK and SFK to enhance weather forecasts, and the recognition of the vital importance of LFK to prevent the loss of this valuable knowledge.

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CRediT authorship contribution statement

S.P. and N.S. conceived and implemented the research. E.A. and S.J.S. contributed substantially to the study design, editing, and

[1] https://www.arcgis.com/apps/mapviewer/index.html?webmap=b5f7b01771cd450bac642853b62bb620.

commenting on the article drafts for several rounds. F.L. contributed to project acquisition and reviewing/editing this submitted manuscript. All authors have read and agreed to the published version of the manuscript.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Spyridon Paparrizos reports financial support was provided by Dutch Research Council.

Data availability

Data will be made available on request.

Appendix A

Annex 1
Overview of research strings during literature review: documentation phase.

Database	Search query	Number of articles
Scopus	(TITLE-ABS-KEY (tradition OR traditional OR traditionally OR indigenous OR local OR locally) AND TITLE-ABS-KEY (forecast OR forecasting OR prediction OR predicting OR predict) AND TITLE-ABS KEY (weather OR climate) AND TITLE-ABS-KEY (agriculture OR agricultural OR farming OR farmer OR husbandry OR pastoralist OR herder OR smallholder OR cultivation OR tillage OR crops)) AND PUBYEAR >2019 AND (LIMIT-TO (LANGUAGE, "English"))	1786
Scopus	(ALL (("local knowledge" AND forecast AND agriculture)) OR ALL (("traditional knowledge" AND forecast AND agriculture)) OR ALL (("indigenous knowledge" AND forecast AND agriculture)) OR ALL (("local forecast knowledge" AND forecast AND agriculture)) OR ALL (("traditional forecast knowledge" AND forecast AND agriculture)) OR ALL (("local forecast knowledge" AND forecast AND agriculture))) AND (LIMIT-TO (LANGUAGE, "English"))	636
Scopus	TITLE-ABS-KEY (("forecasting" OR "forecast" AND "local farmers" AND weather)) AND (LIMIT-TO (LANGUAGE, "English"))	7
Web of Science	(TS = (tradition OR traditional OR traditionally OR indigenous OR local OR locally) AND TS = (forecast OR forecasting OR prediction OR predicting OR predict) AND TS = (weather OR climate) AND TS = (agriculture OR agricultural OR farming OR farmer OR husbandry OR pastoralist OR herder OR smallholder OR cultivation OR tillage OR crops)). Refined by: Languages: English	1516

Annex 2
Literature overview.

Continent	Country	Location/region	Sample size	References
N. America	Mexico	The State of Tlaxcala	30 Individuals interviewed (semi-structured interview), participant observations and participatory workshop (with open questions)	Rivero-Romero et al. (2016)
N. America	US	Oklahoma	16 Individuals interviewed (semi-structured interviews and related follow-ups) and 18 participant-observations	Peppler (2011, 2017)
S. America	Argentina	Chubut Plateau (Patagonia)	20 Individuals interviewed (open and semi-structured interviews)	Castillo and Ladio (2018)
S. America	Peru and Bolivia	Andes	Unknown	Orlove et al. (2010)
Asia	India	Kerala (Wayanad District)	100 Individuals interviewed (open-ended questions), 30 key informant interviews and FGDs (Focus Group Discussions)	Bonny and Anju (2019)
Asia	India	Mizoram (Aizawl, Champhai and Saiha districts)	Interviews, group discussions with 5 individuals, personal interaction, and telephone communication	Chinlampianga (2011)
Asia	India	Rajasthan	100 Individuals interviewed	Pareek and Trivedi (2011); Sarkar et al. (2015)
Asia	India	Tamil Nadu (Coimbatore District)	90 Individuals interviewed	Anandaraja et al. (2008)
Asia	India	Himachal Pradesh (Miyar Valley)	73 Respondents interviewed and participated in FGD	Padigala (2015)
Asia	India	Andhra Pradesh (Visakhapatnam District)	60 Individuals interviewed (open-ended interview)	Ravi Shankar et al. (2008)
Asia	India	Andhra Pradesh (Anantapur district)	60 Individuals interviewed (open-ended interview)	Ravi Shankar et al. (2008)
Asia	India	Andhra Pradesh (Ranga Reddy District)	60 Individuals interviewed (open-ended interview)	Ravi Shankar et al. (2008)
Asia	India	Uttarakhand (Johar, Byans, Niti and Bhagirathi Valleys)	871 Individuals interviewed (semi-structured questionnaire), 12 FGDs, 24 in-depth interviews and 30 key informant interviews	Rautela and Karki (2015)
Asia	Malaysia	Sarawak	Informal interviews, participant observation, open-ended interviews and FGDs	Garay-Barayazarra and Puri (2011)
Asia	Myanmar	Mandalay (Dry Zone of Myanmar)	106 Individuals interviewed and key informant interviews	Swe et al. (2015)
Asia	Philippines	Ilocos (Ilocos Norte Province)	204 Individuals interviewed	Galacgac and Balisacan (2009)
Asia	Vietnam	Bac Kan Province (Ba Be District)	10 In-depth interviews (with local representatives), 30 households interviewed and 2 FGDs (5 discussants each)	Son et al. (2019)
Africa	Botswana	Central District (Bobonong Sub-District)	50 Individuals interviewed, FGDs and key informant interviews	Mogotsi et al. (2011)
Africa	Botswana	Kgalagadi North District	40 Individuals interviewed, FGDs and key informant interviews	Mogotsi et al. (2011)
Africa	Burkina Faso	Centre-Nord (Namentenga Province)	23 Households surveyed, 12 individual in-depth interviews, 20 interviews with resource persons	Roncoli et al. (2002)

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Annex 2 (*continued*)

Continent	Country	Location/region	Sample size	References
Africa	Cameroon	Nord-Ouest Province (Bui Plateau of the Bamenda Highlands)	597 Households questionnaires and 8 FGDs (72 participants)	Tume et al. (2019)
Africa	Ethiopia	Afar Regional State	85 Individuals interviewed, 6 FGDs (with each 6 participants)	Balehegn et al. (2019)
Africa	Ethiopia	Oromia Regional State (Borana zone)	200 Households questionnaire, 4 FGD (with an average of 12 participants each) and 18 in-depth interviews; 80 Households surveyed and 20 critical interviews	Ayal et al. (2015); Iticha and Husen (2019)
Africa	Ethiopia	Oromia Regional State (Arsi Negele District)	355 Households interviewed, 18 FGDs and 30 key informant interviews	Mekonnen et al. (2018)
Africa	Ethiopia	West-Central Ethiopia (Dejen) Nile Basin	398 Households surveyed, FGDs and key informant interviews	Amare (2018)
Africa	Ghana	Western Region (Aowin-Suaman district)	Questionnaires, FGDs and key informant interviews	Gyampoh et al. (2011)
Africa	Ghana	Volta Region (Keta)	Questionnaires, FGDs and key informant interviews	Gyampoh et al. (2011)
Africa	Ghana	Upper East Region (Talensi-Nabdam District)	Questionnaires, FGDs and key informant interviews	Gyampoh et al. (2011)
Africa	Ghana	Upper West (Wa West District)	Questionnaires, FGDs and key informant interviews	Gyampoh et al. (2011)
Africa	Ghana	Northern Region (West Mamprusi District)	93 Questionnaires, FGDs and key informant interviews	Gyampoh et al. (2011)
Africa	Ghana	Northern Region (Zabzugu-Tatale District)	94 Questionnaires, FGDs and key informant interviews	Gyampoh et al. (2011)
Africa	Ghana	Greater Accra (Ada East)	5 FGDs (5–9 participants) and 32 individual interviews	Gbangou et al. (2021)
Africa	Kenya	Laikipia County	133 Individuals questionnaires and 1 FGD (24 participants)	Vervoort et al. (2016)
Africa	Kenya	Vihiga County	111 Individuals questionnaires and 1 FGD (24 participants)	Vervoort et al. (2016)
Africa	Kenya	Lake Victoria Basin	240 Individuals questionnaires and 4 key informant interviews	Kipkorir et al. (2012)
Africa	Kenya	Isiolo County (Borana community)	400 Households questionnaires and 2 FGDs (2 groups × 10 participants)	Kagunyu et al. (2016)
Africa	Kenya	Makueni County	127 Households questionnaires, key person interviews, workshops and FGDs	Speranza et al. (2010)
Africa	Malawi	Southern Malawi (Chikhwawa)	10 Key informant interviews, 3 FGDs (15–20 participants) and 19 households surveyed	Nkomwa et al. (2014)
Africa	Mali	Inner Niger Delta	194 Individuals questionnaires	Zare et al. (2017)
Africa	Mozambique	Gaza (Chibuto and Guija Districts)	25 FGDs (6–8 participants each group); 12 key informants interviews	Salite (2019)
Africa	Nigeria	The Delta State (Isoko Area)	11 Individuals in-depth interviews, 6 FGDs (between 3 and 12 participants)	Ebhuoma and Simatele (2019); Fitchett and Ebhuoma (2018)
Africa	Nigeria	North Nigeria (Kaduna, Kano, Sohoko and Bauchi States)	25–60 Individuals semi-structured interviews and FGD	Sanni et al. (2012)
Africa	South Africa	KwaZoeloe-Natal (Umgungundlovu District)	100 Households questionnaires and 3 FGDs (15 participants each group)	Basdew et al. (2017)
Africa	South Africa	Mpumalanga (Ehlanzeni district)	90 Individuals key informant interviews, 8 FGDs (with between 8 and 12 participants) and 8 key informant interviews	Ubisi et al. (2020)
Africa	South Africa	Free State	394 Individuals in workshop and 130 individuals interviewed	Zuma-Netshiukhwi et al. (2013)
Africa	Tanzania	Tanga Region (Lushoto District)	77 Individuals interviewed	Mahoo et al. (2015)
Africa	Tanzania	Morogoro and Iringa Regions	120 Individuals questionnaires and 4 FGDs (consisting of 8 participants)	Kijazi et al. (2013)
Africa	Tanzania	Mbeya Region and Iringa Region (South-Western Highlands)	53 Individuals interviewed and 1 FGD (up to 8 participants)	Chang'a et al. (2010)
Africa	Tanzania	Dodoma Region (Western foot slopes of the Burunge Hills) (Kondoa District)	120 Individuals questionnaires	Slegers (2008)
Africa	Tanzania	Singida Region (Maluga village)	84 Individuals interviewed, 2 in-depth interviews and 1 FGD (consisting of 8 participants)	Elia et al. (2014)
Africa	Tanzania	Dodoma Region (Chibelela village)	84 Individuals interviewed, 2 in-depth interviews and 1 FGD (consisting of 8 participants)	Elia et al. (2014)
Africa	Uganda	West and Central Uganda (Hoima District and Rakai District)	120 Households interviewed and FGDs	Radeny et al. (2019)
Africa	Uganda	Mt. Elgon region (Bududa District and Manafwa District)	255 Individuals semi-structured interviews & 12 FGDs (123 participants)	Kyazze et al. (2019)
Africa	Uganda	Lake Victoria BASIN (Isingiro District and Rakai District)	164 Households questionnaires, 4 FGDs (10–15 participants) and key informant interviews	Tolo et al. (2014)
Africa	Zambia	Southern Province (Sinazongwe District)	Baseline survey and group interviews	Kanno et al. (2013)
Africa	Zimbabwe	Mashonaland East	20 Individuals questionnaires and 10 FGDs	Tanyanyiwa (2018)
Africa	Zimbabwe	Masvingo (Chiredzi District)	100 Individual questionnaires, FGD and key informant interviews	Jiri et al. (2015)
Africa	Zimbabwe	Matabeleland North (Binga district) (Batonga people)	20 Individuals open-ended interview	Siambombe et al. (2018)
Africa	Zimbabwe	Mashona Central (Mbire District) (Zambezi Valley)	7 Key informant interviews, 5 FGDs (7–15 participants per focus group) and 181 individual semi-structured questionnaires	Alvera (2013)

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Annex 2 (*continued*)

Continent	Country	Location/region	Sample size	References
Africa	Zimbabwe	Mzingwane Catchment (Beitbridge, Mangwe, Esighodini and Mwenezi Districts)	101 Individuals structured questionnaires, 8 FGDs (5–10 per group) and key informant interviews	Chisadza et al. (2013)
Africa	Zimbabwe	Mashonaland Central (Guruve District)	40 Households questionnaires, 2 FGDs (15 participants in each group) and 6 key informant interviews	Gwenzi et al. (2016)
Africa	Zimbabwe	Midlands (Mberengwa District)	79 Individuals questionnaires, 2 FGDs (FGD with 20 participants and FGD with 16 participants) and 6 individuals key informant interviews	Shoko and Shoko (2013)
Africa	Zimbabwe	Mashonaland east (Murehwa District)	30 Individuals surveyed (questionnaires, in-depth interview, FGDs)	Soropa et al. (2015)
Africa	Zimbabwe	Matabeleland North (Tsholotsho District)	31 Individuals surveyed (questionnaires, in-depth interview, FGDs)	Soropa et al. (2015)
Africa	Zimbabwe	Masvingo (Chiredzi District)	25 Individuals surveyed (questionnaires, in-depth interview, FGDs)	Soropa et al. (2015)

Annex 3
Category of indicators and their indication in relation to local weather forecasting.

Category of indicators	Indication in relation to indigenous weather forecasting
Animal	**Birds:** - The appearance of the Akpo (local name) in early January indicates that rain will be good for the subsequent seasons in the Volta Region of Ghana (Gyampoh et al., 2011). - Good rains are expected when an increased presence of quelea birds and sparrows is observed in Central District of Botswana (Mogotsi et al., 2011). - Rain or bad weather is predicted when flocks of birds fly below their normal flight height; when they fly high in the sky it is an indication of good weather in Uttarakhand of India (Rautela and Karki, 2015). - The movement of migratory birds from east to west indicates the onset of rains, while west to east movement indicates the cessation of rains In the Mt. Elgon region of Uganda (Kyazze et al., 2019). - Rains are expected at any given time during the season when the singing of the black cuckoo is heard in Andhra Pradesh of India (Ravi Shankar et al., 2008). - Normal rain is imminent during May or June when the ground hornbill sings frequently in the Mzingwane Catchment of Zimbabwe (Chisadza et al., 2013). - The unusual chirping of certain birds is an indication of upcoming rain in llocos Norte of Philippines (Galacgac and Balisacan, 2009). - Rain is expected to be scarce when the openings of bird nests are directed towards the sky, and when the opening of the nest faces the ground, rains are expected to be abundant in the Inner Niger Delta of Mali (Zare et al., 2017). - More information can be found in Supplementary Table A.1. **Insects:** - The appearance of ants is an indication of expected or imminent rainfall and a good season in Laikipia County and Vihiga County of Kenya, Rajasthan of India, and the South-Western Highland of Tanzania, (Chang'a et al., 2010; Pareek and Trivedi, 2011; Sarkar et al., 2015; Vervoort et al., 2016). - Drought is forecasted when termites stop gathering and storing food and building hills. In this case, gathering and storing food is an indication that a normal rainfall season is expected in Oromia Regional State (Ethiopia) (Ayal et al., 2015). - Rainy weather is expected when termites stockpile grass In Mashonaland East of Zimbabwe (Tanyanyiwa, 2018). - Rain is predicted when low-flying dragonflies are observed in both Tamil Nadu of India and Ilocos Norte of Philippines, (Anandaraja et al., 2008; Galacgac and Balisacan, 2009). - Rain is predicted when dragonflies in swarms are observed in Andhra Pradesh of India (Ravi Shankar et al., 2008). - The appearance of butterflies is an indication of early rainfall and a good season, and the appearance of black butterflies at a particular time is an indication of a very good rainfall season in the South-Western Highlands of Tanzania (Chang'a et al., 2010). - An early rainfall is expected when the appearance of butterflies is observed in Rajasthan of India (Pareek and Trivedi, 2011; Sarkar et al., 2015). - The migration of butterflies is an indication of rainfall in Vihiga County and Laikipia County of Kenya (Vervoort et al., 2016), - Early rains and a good rainy season are expected when the migration of butterflies from the south to the north is observed in the Tanga Region of Tanzania (Mahoo et al., 2015). - More information can be found in Supplementary Table A.2. **Mammals:** -Cattle jumping, flapping their ears, and bellowing on dry riverbeds are often used as indications that rain is expected (Mahoo et al., 2015; Ravi Shankar et al., 2008; Tanyanyiwa, 2018). - A storm is predicted when cattle are becoming sensitive and remain in the woods in Oklahoma of USA (Peppler, 2011). - Cattle is also used to predict drought is when it look back for their calves and blow after milking and leaving home in Ethiopia (Iticha and Husen, 2019). - Sheep, Cattle and goats are frequently used as indicators; most of the indicators concern predictions on rain and snow signals at Chubut Plateau of Argentina. There, snow is expected when herds of sheep and goats return from the plateau (Castillo and Ladio, 2018). -Other wild animals, like elephants and lions, are used by just a few people, mainly in Zimbabwe and Botswana. - For more animals, like dogs, cows, camels, and pigs, see the description in Supplementary Table A.3. **Amphibians:** - Rainfall is expected when a gecko sings “tauk te” eight times, and when a gecko sings more or lesser than eight times, the prediction is that rainfall may be far away in the Dry Zone of Myanmar (Swe et al., 2015). - The croaking of the frogs indicates good rains in the season. However, just seeing the frogs sometimes is enough to make this prediction in the Upper West Region of Ghana, (Gyampoh et al., 2011). - For more information on Spiders, Annelids, Reptiles, and Centipedes that are used by farmers for weather forecasting, please see Supplementary Tables (Tables A.4–A.11).
Meteorological	**Wind:** - Rain is expected when strong winds exist in the Tanga Region of Tanzania, while in the South-Western Highlands of Tanzania, decreased rainfall in the upcoming seasons is expected when strong winds occur from July to October (Chang'a et al., 2010). - Wet seasons are expected when easterly winds around August are strong and dry season is expected when they are weak in Mpumalanga of South

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Annex 3 (*continued*)

Category of indicators	Indication in relation to indigenous weather forecasting
	Africa (Ubisi et al., 2020). - Farmers predict rain within 3 to 5 h when the wind moves towards the sun in the Northern Region of Ghana, (Gyampoh et al., 2011). -Farmers use the occurrence of whirlwinds to predict early or coming rains in Kerala of India, the Dodoma Region of Tanzania, and Mashonaland East and the Midlands in Zimbabwe, (Chisadza et al., 2013; Shoko and Shoko, 2013; Slegers, 2008; Tanyanyiwa, 2018). - The appearance of whirlwinds is an indication of the onset of the dry season in the Mzingwane Catchment in Zimbabwe, (Bonny and Anju, 2019). - When the Harmattan it occurred until January indicates adequate rainfall in the forthcoming planting season but when it extends until February or March, it is expected that lower rainfall will occur in the forthcoming planting season in the Delta State in Nigeria (Ebhuoma and Simatele, 2019; Fitchett and Ebhuoma, 2018). **Clouds:** - The presence of white clouds indicates the cessation of rains, and dark clouds indicate the onset of rains in the Mt. Elgon region of Uganda (Kyazze et al., 2019). - Heavy rains are predicted when dark clouds are observed in the Nord-Ouest Province of Cameroon (Tume et al., 2019). - Rainfall is predicted by observing red clouds and in the Northern Region of Ghana (Gyampoh et al., 2011). -Stratus clouds are used to predict cold days In the Free State of South Africa (Zuma-Netshiukhwi et al., 2013). - Drought is expected when nimbus clouds appear in the daytime but disappear at the night in Makueni County of Kenya (Speranza et al., 2010). - The appearance of nimbostratus and cumulonimbus clouds indicate a high probability of rainfall In West and Central Uganda (Radeny et al., 2019). - Rain is expected on the same day when clouds moves rapidly from west to east. When the cloud moves slowly from west to east, rain is predicted to occur the next day in the Oromia Regional State in Ethiopia (Mekonnen et al., 2018). - Heavy rain is predicted in two days when the clouds layer moves in a north-to-south direction in Bac Kan in Vietnam (Son et al., 2019). **Temperature:** - Good rains are expected when high temperatures are observed at night. Whereas, low temperatures during the night indicate a late onset of rains in the Free State in South Africa (Zuma-Netshiukhwi et al., 2013). - Drought is expected when it is very hot throughout the year in Gaza of Mozambique (Salite, 2019). - Drought is predicted in the coming season when the winter is warmer than normal in Mashonaland East in Zimbabwe (Alvera, 2013). - When it is cold in the morning in the Dodoma Region of Tanzania, no rain is expected soon (Slegers, 2008). - Good rainfall season from September to October is predicted when there is very hot weather in the Midlands in Zimbabwe (Shoko and Shoko, 2013). - Rain is expected within the late afternoon when there are unusual increases in heat In West-Central Ethiopia (Amare, 2018). - For a literature overview of all indicators based on meteorology, see supplementary Table B.
Astronomical	**The Moon:** - Good rainfall season is predicted when a halo is observed around the moon in many parts of Africa, and Asia and North America. - A halo around the moon indicates that hot and dry weather are expected in several days in Vietnam (Son et al., 2019). - Rain is unlikely to occur when a full moon is observed in the Midlands region of Zimbabwe. A full moon indicates that no rain and dry conditions are expected in Mashona Central and Mashonaland East (Tanyanyiwa, 2018). - A red moon in the Tanga Region in Tanzania indicates the onset of rain in the short rainy season, while a white moon indicates the onset of rain in the long rainy season (Mahoo et al., 2015). - When the moon has beige tones, a dry season is expected, and if the moon is completely white, abundant rainfall is expected In Central America and specifically in Tlaxcala in Mexico (Rivero-Romero et al., 2016). **Stars:** -Drought is expected when numerous stars in the sky are observed or when the stars are dispersed across the sky in the region of Gaza in Mozambique (Salite, 2019). - The observation of a constellation of seven stars that appear in the east indicates that drought is expected in Makueni County in Kenya (Speranza et al., 2010). **Sun:** -Rains are expected when there is a presence of a ring/halo around the sun in Greater Accra (Ghana), Mashonaland East (Zimbabwe), Midlands (Zimbabwe), Himachal Pradesh (India), and Uttarakhand (India) (Gbangou et al., 2021; Padigala, 2015; Rautela and Karki, 2015; Shoko and Shoko, 2013; Tanyanyiwa, 2018). -The observation of high-intensity sunshine gives a prediction of upcoming rain, which is expected within one to seven days in the Greater Accra region in Ghana (Gbangou et al., 2021). -The shading of the sun is also used to predict that a season will not be affected by drought conditions In Makueni County in Kenya (Speranza et al., 2010). -For more indicators on astronomy, see Supplementary Table C.
Plants	- In Rajasthan (India) and the South-Western Highlands in Tanzania, both the flowering and generation of new leaves on Ficus and fig trees indicate that rainfall is predicted (Chang'a et al., 2010; Pareek and Trivedi, 2011). - The late flowering of Msasa or Munhondo plants indicates that a drought year can be expected in Mashonaland East of Zimbabwe (Soropa et al., 2015). - The ripening and early rotting of the fruits of the Jambolan provide a prediction of the onset of a rainy season in Ilocos Norte at the Philippines (Galacgac and Balisacan, 2009). - When more fruits are produced by the guava tree, fig tree, and marula tree, a good season with an abundance of rain is expected in Mpumalanga at South Africa (Ubisi et al., 2020). - A few fruits produced by the edible Gigerwort crop suggest low rainfall amounts for the coming year in the Dry Zone of Myanmar (Swe et al., 2015). - In supplementary Table D, all the details and descriptions of indicators based on plants for farm decision-making can be found.
Other uncategorized indicators	- When the intestines of slaughtered animals have red colour, it is an indication that it will rain. And black colour of intestines mean a foreseen drought in the Borana community at Isiolo County in Kenya (Kagunyu et al., 2016). - A pure fluid inside the intestine indicates that good rains are expected in the coming season, while a turbid colour indicates above-normal rain or even flooding in the Oromia Regional State of Borana zone (Ayal et al., 2015; Iticha and Husen, 2019). - When there is little food in the small and large intestines, it means a drought season is expected and a large amount of food found in the intestines implies normal rainfall. A moderate amount of food indicates a small rainfall season is expected (Ayal et al., 2015). - When too many baby girls are born, a wet year is expected and vice versa for a drought year in Zimbabwe (Soropa et al., 2015). - Uncomfortable and sweaty feeling indicates rain in few hours to the next day in Ghana, South Africa, and India (Anandaraja et al., 2008; Gyampoh et al., 2011; Ubisi et al., 2020) - Humid or cold weather is predicted when people have pain in their joints or sars in Mpumalanga in South Africa and in India (Ubisi et al., 2020). - In Uttarakhand, India, people also identify the approaching of summer rain by looking at the soil under the stones near a river or a hillside (Rautela and Karki, 2015).

Appendix B. Supplementary data

Below is an overview of the supplementary tables that are accompanying the current study following the Systematic Literature Review. Full tables can be found in the supplementary file. Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2023.165539.

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