Climate Services 39 (2025) 100585

Contents lists available at ScienceDirect

Climate Services

journal homepage: www.elsevier.com/locate/cliser

A Spatial Decision Support System for climate-adapted agriculture designed with and for stakeholders in West Africa

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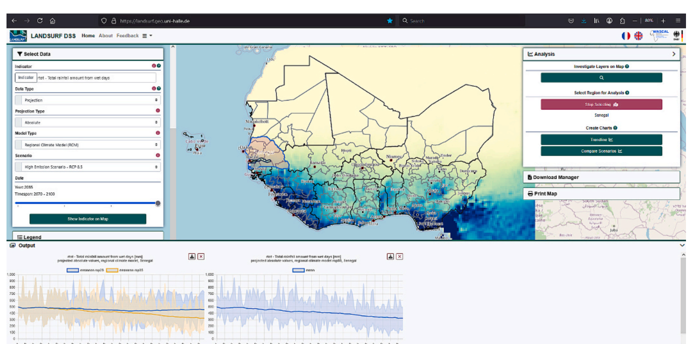
HIGHLIGHTS

- Presentation of a new multifunctional SDSS for agriculture in West Africa.
- Participative approach to select indicators relevant for stakeholders using a nine-step interaction protocol.
- Broad range of easy-to-understand climate, crop, and remote sensing indicators publicly and freely available.
- Results easily scalable from individual grid boxes to various administrative levels.
- Information on the signal-to-noise-ratio of climate change signals within a large model ensemble.

GRAPHICAL ABSTRACT



ARTICLE INFO

Keywords:
Spatial Decision Support System
West Africa
Climate Change
Adaptation Strategies
Stakeholder Co-development
Agriculture
Indicators

ABSTRACT

This paper presents a Spatial Decision Support System (SDSS) designed to assist stakeholders in West Africa in analysing critical climate and land use indicators for risk management in agriculture and further sectors being affected by extreme precipitation and temperature events. Developed as part of the WASCAL WRAP 2.0 project LANDSURF, the SDSS makes scientific data accessible and comprehensible to non-scientific audiences, facilitating informed decision-making among communities affected by climate change. From the beginning of the development process, the web portal was co-designed with relevant West African stakeholders. Due to the challenging conditions during the COVID-19 pandemic, alternative online communication tools, e.g. ZOOM, online surveys and email, successfully were utilized to interact with stakeholders instead of on-site activities. The

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https://doi.org/10.1016/j.cliser.2025.100585
Received 20 December 2024; Received in revised form 7 May 2025; Accepted 4 June 2025
Available online 13 June 2025

co-design process carried out with stakeholders includes several steps such as stakeholder analysis, identification of their information needs using specific climate, crop and remote sensing indicators, and the evaluation of the SDSS in a dedicated workshop. In total, the co-design process involved nine different steps, recorded and described in a stakeholder interaction protocol.

The SDSS integrates observational data, including CHIRPS and ERA5-Land datasets, and state-of-the-art high-resolution climate model outputs under two greenhouse gas concentration scenarios (RCP2.6 and RCP8.5) and remote sensing data. It enables the comparison of model outputs with observations and facilitates the assessment of regional climate variability and trends. Two concept studies illustrate the SDSS's functionality: one focusing on a farmer in Burkina Faso assessing irrigation needs for millet cultivation, and another involving a regional planner analysing drought and heat wave impacts in coastal West Africa. These examples highlight the SDSS's usability in supporting adaptive strategies and enhancing resilience to climate-related challenges, underscoring the importance of integrating local knowledge with scientific data for effective climate adaptation and mitigation.

1. Introduction

West Africa faces growing challenges from climate change, particularly in its agriculture-dependent economies. The region, characterized by its reliance on rain-fed farming systems, is especially vulnerable to shifts in climate. Recent research highlights the increased severity, frequency, and intensity of extreme weather events such as droughts and heatwaves, which are amplified by higher precipitation variability and evapotranspiration rates (Masih et al., 2014; Thomas & Nigam, 2018; IPCC, 2021). These climatic stressors, coupled with rapid population growth and rising pressure on natural resources, pose significant risks to regional food security (Herrmann et al., 2020; Beltran-Peña & D'Odorico, 2022).

The agricultural impacts of climate change in West Africa are projected to be profound. Staple crops such as maize, millet, and sorghum are expected to experience significant yield reductions due to inconstancy of rainfall, changing growing seasons, increased water stress, and the compounding effects of heat and drought (Roudier et al., 2011, Waha et al., 2013; Bangelesa et al., 2023; Gbode et al., 2025). For example, areas impacted by overlapping heat and drought events are anticipated to expand substantially by the late 21st century, intensifying the challenges of maintaining crop productivity (Wang et al., 2023). These impacts are expected to worsen under both low- and high-concentration scenarios, underscoring the urgent need for adaptive strategies (IPCC, 2022).

While Global Climate Models (GCMs) and Regional Climate Models (RCMs) have been instrumental in projecting these changes, they exhibit notable differences in their ability to simulate key climatic phenomena. GCMs provide valuable large-scale insights but struggle with regional details, such as the onset and variability of rainy seasons (Ayugi et al., 2020; Du et al., 2022). RCMs, with their higher spatial resolution, offer an improved representation of localized climatic processes, such as land–atmosphere interactions and precipitation variability (Rummukainen et al., 2015; Prein et al., 2016; Giorgi & Gao 2018), which are critical for calculating agricultural indices like crop water needs and irrigation requirements (Abel et al., 2024). However, RCM outputs also often exhibit systematic biases due to factors such as simplified physical processes or uncertainties in boundary conditions. As a result, expert knowledge about bias correction methods that are commonly applied to RCM data to adjust for these systematic errors before the data are used in impact assessments or as input for other models is necessary.

Climate adaptation and enhanced resilience of the local population requires that information on regional to local climate change is available in a form that is technically low-threshold, free of charge, easy to understand for non-academics, and relevant for decision making. Decision Support Systems (DSS) and web-based Geographic Information Systems (GIS) have emerged as vital tools to bridge the gap between climate data and actionable decision-making (Palutikof et al., 2019a; Talari et al., 2022). These spatial DSS (SDSS) integrate climate and land use data in a processed and simplified way to transfer complex information on their change in a low-threshold and concise manner to provide a decision basis for stakeholders in various fields. These systems can be designed for specific target groups, e.g. agriculture (Paeth et al., 2023), forestry (Czimber & Gálos, 2016), water management (Xia et al. 2014), and health (Fünfgeld et al., 2019), or for a broader audience (Bonfante et al. 2024). Such services are particularly required on the African continent where exposure and vulnerability to climate change is large while the population's resilience is low (Lumbroso et al., 2024).

In the meantime, several DSSs have been developed and opened to the public. To acknowledge this excellent previous work, we mention a few of these approaches, characterizing their strengths and limitations. A benchmark certainly is the *Hand-in-Hand Geospatial Platform* provided by the FAO (https://www.fao.org/hih-geospatial-platform/en/). This platform combines geospatial data with economic and agricultural statistics to assist stakeholders in identifying opportunities for agricultural development, particularly in vulnerable regions. It offers detailed visualizations and analyses of climatic impacts on agriculture, focusing on productivity and food security metrics. However, its global focus implies a limited granularity for region-specific factors in West Africa and does not incorporate local knowledge from smallholder farmers. In addition, (compound) extreme events are underrepresented. The *ClimDev-Africa Initiative* developed under the African Union Commission supports decision-making in climate adaptation by providing data and tools tailored to Africa. Its platform integrates climate projections with sector-specific analyses, enabling targeted interventions in agriculture, water resources, and disaster management (https://www.climdev-africa.org/). Constraints pertain to the data accessibility and usability, particularly for stakeholders with limited technical capacity, and to the low resolution of climate data that may lack sufficient resolution to address smallholder farming needs. While promoting capacity building, implementation at the community level has been slow. The *EU Copernicus Climate Change Service* (C3S) delivers open-access tools and datasets for analysing climate impacts across sectors, including agriculture (https://atlas.climate.copernicus.eu/atlas, https://cds.climate.copernicus.eu/). Its Climate Data Store offers user-friendly interfaces to explore temperature trends, water balance indices, and growing season projections for specific regions, including parts of Africa. The platform provides high-quality data but lacks a focus on specific crops or agricultural practices dominant in West Africa and requires technical expertise for processing and interpretation, making it less accessible to users outside academia or government institutions, such as local stakeholders in West Africa. The *AGRHYMET Regional Centre* in Niger provides climate, hydrological, and agricultural data tailored to the Sahelian region (https://agrhymet.cilss.int/). Its tools support agricultural planning and drought monitoring by delivering seasonal forecasts and early warning information for food security and water resource management. While this service is regionally focused, its tools rely heavily on seasonal averages and forecasts and do not adequately address extreme weather or compound events. The platform also struggles to provide localized solutions for individual farmers or specific micro-climates across West Africa and accessibility remains a challenge for stakeholders without significant training in the platform's use. Finally, the *Famine Early Warning Systems Network* (FEWS NET) is widely used in the region for food security monitoring. It combines climate data, agricultural outputs, and socio-economic factors to provide detailed analyses of potential famine risks and resource needs (https://fews.net/). While effective for famine prediction, FEWS NET does not provide tools for proactive farm-level decisions, such as when to plant or irrigate crops. Its focus on food security at the macro-scale means less emphasis on localized agricultural interventions. Moreover, the system relies on external funding and partnerships, which can limit its operational scope or sustainability in certain regions.

Despite the general usability of DSSs, the understanding of the stakeholders' and practitioners' perspective and how these groups are using the DSS is differently represented when designing such systems (Teucher et al., 2014; Palutikof et al., 2019a; Webb et al., 2019). In addition, some platforms are constrained by their spatiotemporal resolution and the number of available key indicators relevant to agriculture, such as crop water needs and irrigation requirements. Typical key challenges of DSSs are:

- the data accessibility for stakeholders with limited technical capacity and expertise,
- the assumption of expertise knowledge when interpreting the displayed information,
- the presentation of too coarse datasets not meeting the resolution relevant for local stakeholders,
- the lack of relevant indices tailored to specific decision-making processes and stakeholder groups,
- the non-involvement of stakeholders and their specific needs prior to and during the development process of the DSS.

The novel SDSS introduced here aims at addressing most of these challenges. It is designed to provide climate change information to stakeholders from various administrative levels between below-district and international scales across West Africa. The presented SDSS is characterized by basically four innovative elements: (1) It is based on a participative approach to select climate indicators relevant for stakeholders using a thoroughly elaborated nine-step interaction protocol. (2) A broad range of easy-to-understand climate, crop, and remote sensing indicators has been made publicly and freely available, when at least 50 % of the involved stakeholders marked them as being of relevance for their decision making. (3) Results are easily scalable from individual grid boxes to various administrative levels. (4) Information is given on the signal-to-noise-ratio and statistical significance of climate change signals within a large ensemble of high-resolution climate models.

In particular, the SDSS meets the requirements by stakeholders dealing with issues in the climate change-agriculture nexus. However, a broad potential for other sectors of economic, political and social activity is inherent to this system. Note that our SDSS does not provide information on impacts, adaptation, engagement, e.g. in the form of adapted agricultural practices such as crop and seed recommendations, as it is done by some DSSs (e.g., Adaptation Wizard or CoastAdapt). The relevance of the SDSS to the target groups is achieved by a structured participative process that has started in the earliest stage of the project, selecting the information displayed in the SDSS as well as its design (Section 2). By using high resolution climate projections and calculating climate, agricultural, and remote sensing indices, a wide range of stakeholder needs could be addressed (Section 3). The technical implementation with a focus on accessibility, sustainability, and functionality is described in Section 4. In Section 5, two concept studies demonstrate potential use cases of the SDSS before conclusions are drawn (Section 6).

2. Participative approach

The WASCAL WRAP 2.0 LANDSURF project aimed to make scientific data available and applicable to stakeholders in West Africa in a user-friendly way through a SDSS. As the scientific data are mainly of use to the agricultural sector, providing information on, for example, the characteristics of the rainy seasons or the frequency and intensity of precipitation and temperature extremes, the potential stakeholders are decision makers in regional and local government administrations, non-governmental organisations, scientists from various non-climatic disciplines, and farmers. Consequently, this information may also be relevant to decision-makers working in water and risk management who are directly affected by climate change and need to maintain mitigation and adaptation measures in their sector. To shape the SDSS according to the needs of stakeholders, a participatory approach was adopted, involving them in the co-development and co-design of the SDSS from the beginning of the project (Webb et al., 2019). It further ensures that the SDSS is not only scientifically sound but also practically relevant and applicable in terms of real-world questions and scenarios (Palutikof et al., 2019b; Williams & Jacobs, 2021).

To facilitate this, we used online tools such as ZOOM, email, Google Forms, and Google Jamboard to interact with stakeholders in West Africa. In addition, to facilitate stakeholder involvement in future project planning to co-develop and co-design a similar SDSS or another type of web portal, the different steps taken in this project were documented in an 'interaction protocol' (Weber et al., 2023).

Nine steps of the co-development and co-design process, involving the stakeholders of the LANDSURF SDSS, are described in the following (taken from Weber et al., 2023) (Fig. 1): First, we defined the purpose of the SDSS. This can be done by answering the questions: What kind of information should the SDSS provide and for which sector? And more importantly, to whom should the SDSS be addressed? This was conducted in the second step, where we decided to contact the following stakeholders with a specific contact form: Governmental representatives, who are contact people for the National Adaptation Plans (NAP) to the United Nations Framework Convention on Climate Change (UNFCCC), National Meteorological Services, National Emergency Management Agencies, National Hydrological Agencies, Environment Protection Agencies, National Ministries of Environment and National Ministries of Agriculture, universities in West Africa, and farmers.

To obtain basic information from the stakeholders, a contact form was developed (step three). They were asked for the name of the organisation/company and the name of a contact person, the sector they work in, their level of knowledge about climate and initial questions about their needs for climate information/data. For reasons of efficiency, we used Google Form to develop a questionnaire, which facilitated the stakeholder analysis. The contact form (in English and French) was emailed to potential stakeholders using the network of the project partners and the WASCAL Competence Centre, along with a brief description of the project, explaining the aim of the project, the role of the stakeholders, and the benefits of their involvement.

In total, we received 55 responses from stakeholders from countries in West Africa and beyond, which were analysed to provide detailed information about the stakeholders involved (step four). The majority of the stakeholders were from governmental institutions and universities in the fields of agriculture, environment, and risk management. This database of stakeholders served as a network through which we conducted surveys and invited people to workshops to co-develop and co-design the SDSS. Many stakeholders had little or limited knowledge of climate change and are active in different sectors. Therefore, in step five, we build a reference database of different climate indicators collected from the literature relevant to agriculture, food security, and risk management, before asking stakeholders about their climate information needs. In total, we collected 59 indicators, including those suggested by stakeholders in the first stakeholder workshop (step six).

The first stakeholder workshop was held in the initial year of the project using the videoconferencing platform ZOOM. The stakeholders were asked to participate in ZOOM surveys and to fill out a prepared Google Jamboard to indicate their information needs and the desired

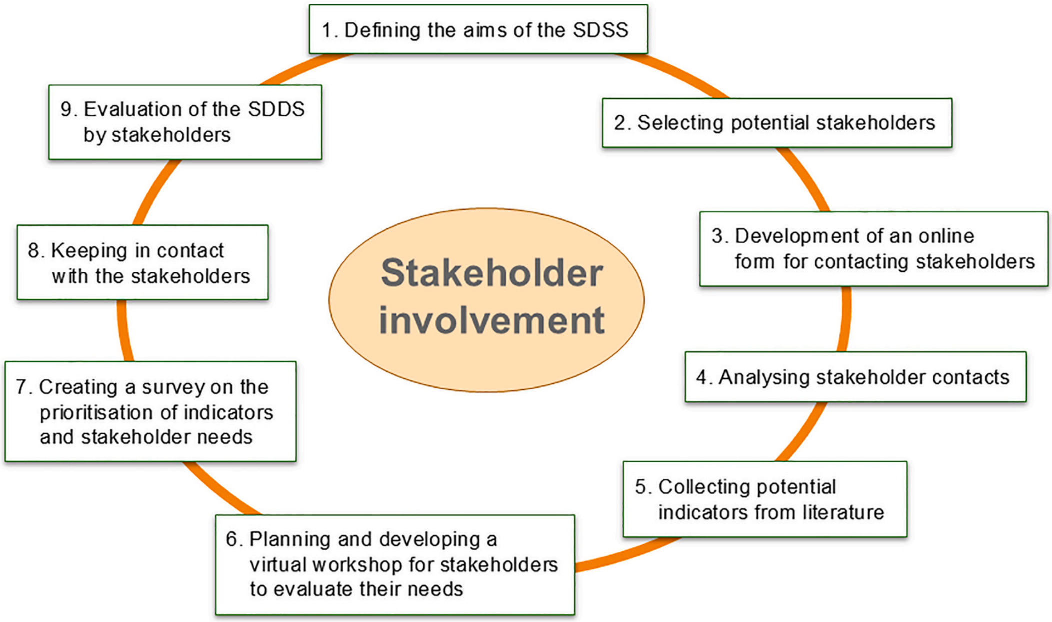

Fig. 1. Interaction protocol diagram.

features of the planned SDSS. We received a lot of valuable information from the stakeholders in the virtual workshop format. In principle, an on-site workshop with face-to-face contact to get to know each other better would be preferable to build trust between scientists and stakeholders. However, the virtual format of the workshop facilitated the participation of a greater number and wider range of stakeholders from different countries and professional backgrounds, eliminating the barriers of travel and related expenses. This inclusive approach represents an advantage independent of the pandemic situation prevailing during that time of the project's funding period.

In step seven, we developed an online survey using Google Forms to prioritise the indicators collected from the literature (step five) and those identified by stakeholders in the first stakeholder workshop (step six). This was necessary for the clarity of the SDSS given the large number of climate indicators we collected. In the survey, climate indicators were categorised into different groups such as rainfall, rainy season and drought indicators, temperature and extreme temperature indicators, irrigation and crop indicators, and other indicators. This made it possible to limit the choice of climate indicators by stakeholders, who were asked to select only certain indicators from a larger number in each category. Respondents were also asked more detailed questions about the design and operation of the SDSS. The bilingual (English/French) survey was then distributed by email to the members of our stakeholder database. Based on the results of the survey, a total of 28 climate indices were selected and processed for the SDSS, with a selection rate of at least 50 % from the stakeholders' perspective.

The co-development and co-design of the LANDSURF SDSS was an ongoing process with stakeholders. Thus, we kept in touch with our stakeholders throughout the project (step eight). To bridge the time between the survey of the indicator prioritisation and the upcoming SDSS evaluation workshop, we distributed a project news update (in English and French). After incorporating the indicators and the characteristics of the SDSS identified by the stakeholders, we organised and conducted a virtual SDSS evaluation workshop with 28 participants from Burkina Faso, Ghana, Niger, Nigeria, Togo, and Germany (step nine).

Stakeholders had the opportunity to test a beta version of the SDSS prior to the workshop and to comment on the content and usability of the system on a Google Jamboard. The workshop was divided into three parts. First, the results of the stakeholder surveys and the development status of the SDSS were presented to the participants. This was followed by an introduction to the content of the SDSS and a demonstration of the potential applications of the SDSS through individual use cases. The third part of the workshop was a moderated interactive session to get feedback from the users of the SDSS. Starting point for the discussion was the Google Jamboard, where users of the SDSS had previously shared their experiences with the system. In addition, several ZOOM surveys were used during the workshop to get answers to specific questions and to assess user satisfaction with the SDSS. For example, users indicated that 2/3 of them had already tested the SDSS before the workshop, and practically all users liked the visualisation of the results, rating it a 4 on a scale of 1 to 5 on average.

Finally, feedback from users on their opinions and experiences with the beta version of the SDSS received during the evaluation workshop was incorporated into the system. We included trend and uncertainty information, removed bugs related to displayed content as well as the underlying data structure, and provided a short but conclusive documentation on the indicators and the underlying data designed for non-scientific users. The final SDSS-version (https://landsurf.geo.uni-halle.de) was launched and presented to the stakeholders in summer 2024. According to comparable initiatives, we can confirm that the number of stakeholder responses decreased over the course of the project. It is not clear whether this is due to the virtual communication we used, or to the 'stakeholder fatigue' that is increasingly common as stakeholder engagement increases.

In general, stakeholders from government organisations are easier to address via the virtual/electronic nature of stakeholder communication that we had to choose due to the pandemic situation. However, they are in close contact with farmers and have shared their needs with us during the SDSS development stages. The now available SDSS is easily accessible by smartphones that are wide-spread among farmers and other individuals in West Africa. The tool is free and open for everyone to use.

3. Data and indices

To achieve the presented goals and fulfil the stakeholders' needs, a broad range of data and indices was considered. By integrating observational data with climate model outputs under two greenhouse gas concentration scenarios, we provide a comprehensive analysis of climate indices and their trends and implications for West Africa during past decades and until the end of the 21st century. This methodological framework not only enhances the understanding of climate dynamics but also supports the development of effective strategies for climate adaptation and mitigation. The climate data as well as the derived indices and the climate model validation are described in more detail in Abel et al. (2024) while Ziegler et al. (2024c) analysed how the respective climate indices develop under the greenhouse gas concentration scenarios available in the SDSS during the 21st century. The processed data and indices as described subsequently are published by Ziegler et al. (2024a, 2024b).

3.1. Data

The calculation of indices is based on two data families: observational and model-derived data. The observational data are further separated into remote sensing and climate data. The first relies on optical satellite images with various spatiotemporal resolutions, i.e., Moderate Resolution Imaging Spectroradiometer (MODIS; Didan, 2021) and Advanced Very High Resolution Radiometer (AVHRR; Earth Resources Observation and Science (EROS) Center, 2018). While spatially higher resolved MODIS data is available since 2003, utilized AVHRR data, which comes in a more coarse spatial resolution, reaches back until 1981. The second incorporates Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS; Funk et al., 2015) and reanalysis data from the European ReAnalysis 5 Land (ERA5-Land; Muñoz-Sabater et al., 2021). CHIRPS provides high-resolution precipitation estimates by combining satellite-based observations with ground-based rain gauge measurements, offering a robust representation of precipitation patterns across various regions at 0.05° resolution. This dataset is particularly valuable for understanding historical precipitation trends and anomalies. In addition, we incorporate ERA5-Land which is a comprehensive climate dataset that includes a wide array of variables such as temperature, precipitation, humidity, and more at a resolution of 0.1°. This dataset is a reanalysis, where a weather forecast model is nudged to actual multi-source measurements, ensuring a high degree of accuracy and reliability. The combination of these two datasets allows for a detailed examination of climate patterns over time. These observational climate data are displayed in the SDSS for the period 1981–2010.

In addition to this, we utilise climate model data covering the period 1981–2100 (an overview table of used models in Supplementary S1). According to the stakeholders' recommendation, they include Global Climate Models from the Coupled Model Intercomparison Project Phase 5 (CMIP5; Taylor et al., 2012) and Regional Climate Models from the Coordinated Regional Climate Downscaling Experiment – Coordinated Output for Regional Evaluations (CORDEX-CORE; Giorgi et al., 2022) to highlight the added value of higher-resolution models. Both model families represent comprehensive physical models either directly calculating or parameterising atmospheric and land surface processes. GCMs from CMIP5 have a spatial resolution of 180 km to 250 km. Here, we only consider a subset of the CMIP5 ensemble, which was used to force the respective RCMs from CORDEX-CORE, to obtain comparability between the two model families. In fact, MPI-ESM (Giorgetta et al., 2013) in low and medium vertical resolution as well as NorESM-M1 (Bentsen et al., 2013) were used while HadGEM2-ES (Jones et al., 2011) and the RCM simulations forced by this model were dismissed due to their reliance on a 360-day calendar being not in line with the examined indices acting on a daily scale. The used RCMs REMO (Jacob et al., 2012; Jacob & Podzun, 1997; Remedio et al., 2019), CLM (Sørland et al., 2021), and RegCM (Giorgi et al., 2012) have a common spatial resolution of 25 km. These models are particularly useful for capturing local climate characteristics due to their high spatial resolution. Additionally, their output acts on a spatial scale that is relevant for decision-makers, enabling responsible science and physically based decisions. The climate data covers the period 1981–2100 where the historical time 1981–2010 acts as the reference period and 2011–2100 serves as future projection period. For the future, two different Representative Concentration Pathways (RCPs; van Vuuren et al. 2011) of greenhouse gases are assumed: RCP2.6, representing a low-concentration scenario, and RCP8.5, a high-concentration one. These scenarios are available for a large number of models in the database. They span the range of potential future climate pathways and provide a framework for assessing the resulting climate impacts by informing decision-making processes based on the SDSS. Note that the involved stakeholders asked for the whole range of concentration scenarios to cover all potential future pathways of regional climate change in West Africa.

In total, the ensembles used within the SDSS are comparatively small with three GCM and six RCM simulations. Thus, the ensemble spread and variability as well as the mean are affected. Nonetheless, Abel et al. (2024) showed that the small ensembles simulate the climate in the study region with a good quality and, thus, may also offer reliable projections of the future.

3.2. Indices and data processing

As described in Section 2, the indicator selection for the SDSS was based on a stakeholder survey to display indicators that are of practical relevance. The indicators can be classified into the three categories 'climate', 'crop', and 'remote sensing', resulting in 28 different indicators (overview table in Supplementary S2).

3.2.1. Climate and crop indices

The climate and crop indices used in this study are derived from climate data, which can be categorised as either observational or model-based.

Preprocessing. It is important to note that for GCMs and observational data, the coordinates are regular and equidistant. However, this regularity does not hold true for RCMs. In the case of RCMs, the variables for longitude and latitude coordinates are two-dimensional due to their conversion into a rotated coordinate system during modelling. This transformation results in an equidistant grid, but when the model output is re-rotated to a regular grid, the longitude and latitude coordinates become non-equidistant. Therefore, after calculating the corresponding index per model a spatial Nearest Neighbour interpolation to a common grid (NorESM for GCMs and CLM for RCMs) using the Climate Data Operators (CDO; Schulzweida, 2023) was necessary to be able to build coherent model ensembles.

Climate and crop indices. All indices (Supplementary S2) are calculated annually based on daily input data of precipitation amounts as well as maximum, minimum, and mean daily temperatures at each grid point. The requirement for multiple temperature variables explains why certain indices cannot be computed using the CHIRPS dataset, as it provides only precipitation data. In contrast, the ERA5-Land dataset offers observational input for all indices, making it a valuable resource for our analysis. Consequently, all indices only using precipitation as input data are available for two observational datasets, while the others are only available with ERA5-Land. Indices of temperature and precipitation which are either counting statistics of specific occurrences per time, like the number of rainy days (*rd)* per year or percentile-based ones (e.g., maximum temperatures exceeding the 90th percentile *tx90p*) are based on the Expert Team on Climate Change Detection Indices (ETCCDI; Zhang et al., 2011). Additionally, more complex indices of heat, like the Heat Wave Duration Index (HWDI; Frich et al., 2002), and drought, like the Standardized Precipitation Index (SPI; McKee et al., 1993) and the Standardized Precipitation Evapotranspiration Index (SPEI; Beguería et al., 2010; 2014; Vicente-Serrano et al., 2010), are provided. Further, a selection of 12 different crops was made according to the stakeholders' suggestions. The corresponding four growth stage parameters necessary for the crop indicators are depicted in table Supplementary S3 (Allen et al. 1998). The beginning of the first growth stages depends on the onset of the first rainy season.

Calculation of the rainy season. For the calculation of the rainy season onset, we employed the method outlined by Dunning et al. (2016), a more specialised form of Liebmann et al. (2012), with modifications following Weber et al. (2018), as described in Abel et al. (2024). It is based on the calculation of accumulated daily precipitation anomalies, where the minimum (maximum) indicates the onset (cessation) of the rainy season. This approach allows for the detection of not only the first rainy season but also a second rainy season that may occur in certain regions by detecting a second minimum and maximum, respectively.

In the first step, the long-term mean cumulative sum of the daily rainfall anomaly is determined at each grid box and subsequently smoothed using a 30-day running mean. The minimum (maximum) of the mean cumulative daily rainfall anomaly is considered the onset (cessation) day of the mean rainy season when the onset (cessation) day is lower (higher) than the four preceding and four following days. If neither a minimum nor a maximum is identified, the smoothing period is extended by 15 days until an equal number of minima and maxima is detected. If this is not achieved, a 120-day running mean is applied. In this context, we assume that the first maximum following a preceding minimum defines a rainy season (Weber et al., 2018). If more than two rainy seasons are detected, only the two longest rainy seasons are considered. Additionally, if the number of days between two rainy seasons is less than 40 or if two rainy seasons overlap, only one rainy season is assumed.

In the second step, the onset and cessation of the rainy season are determined for each individual year. This is accomplished by calculating the cumulative rainfall anomaly (daily rainfall minus climatological daily mean rainfall over the period) and searching for the absolute minimum/maximum within a window of 20 days prior to the climatological onset date and 20 days after the climatological cessation date for each year.

In addition to daily precipitation indices on the annual scale, as defined by the ETCCDI, we also calculate these indices for the rainy season, e.g. the number of rainy days within the rainy season *rdrs* (cf. Table S1). This allows a more detailed assessment of changes and provides deeper insights into this season being of major importance for agriculture and crop practices. For example, not only the information on how long dry periods without precipitation become during a year (*cdd*), mostly during the dry season, is provided, but also the length of a dry period within the rainy season (*cddrs*), adding substantial value for stakeholders with respect to potential breaks during the rainy season.

Post-Processing. Subsequently, the ensemble mean, minimum, maximum, and inter-model standard deviation were calculated for each pixel and each year. To reduce higher-frequency variability, facilitate the construction of climatologies ($\geq$30 years) and improve comparisons among periods, a 30-year running mean ($\pm$15 years) was applied to the ensemble means. This is also important since the GCMs and the RCM simulations forced by GCMs don't have a temporal phase relationship with observations due to their random initial conditions.

Available statistical values in the SDSS. The SDSS provides several key values that are essential for interpreting climate data and their implications. These values are derived through a series of steps to ensure stakeholders' needs:

- Absolute Values (only for observations): The absolute values represent the yearly value of each index at every pixel within the observational datasets. These values are calculated after the post-processing steps, providing a clear representation of the data for each year.
- Historical Mean of Absolute Values: This metric is the average of the absolute values over the period 1981–2010 for each index and data family. It serves as a baseline for comparison, allowing researchers to assess changes over time relative to historical data.
- Difference to Historical Value: This value is calculated by subtracting the historical mean (1981–2010) of the absolute values from the yearly absolute values for each index and data family. It highlights the deviation of annual data from the climate during this reference period, providing insight into trends and anomalies in the past and future.
- Bias-Adjusted Absolute Value for Model Data: To remove systematic errors (biases) in both GCMs and RCMs, all model data undergo a bias adjustment. This is achieved by using the Delta Change Approach (Maraun & Widmann, 2018) which adds the difference between the future mean model data and the historical mean model data to the historical mean of the reference data, ERA5-Land. This method assumes that the model bias at each pixel remains constant over time. By subtracting the historical mean, we eliminate these biases and present adjusted values that emphasise the modelled change over time. This approach allows for a clearer understanding of projected changes while maintaining the integrity of historical observational data. The ERA5-Land data serves as a baseline for representing absolute values, with modelled changes added to reflect absolute future projections rather than merely showing differences since these absolute values typically are the basis for planning initiatives.
- Trend (only for model data): The linear trend is represented by the regression coefficient b in the equation $y = b \cdot x + a$, derived from annual values spanning the years 2001 to 2100 for each pixel and index. It is computed using non-bias-adjusted model data, with time serving as the independent variable and the corresponding index value as the dependent variable. To evaluate the significance of the trend, the slope b, is subjected to a two-sided hypothesis t-test at a significance level of 95 % (Wilks, 2020). It is important to note that only statistically significant values of b are displayed in the DSS; the trend for all other pixels is assigned a value of zero.
- Trend-to-Noise Ratio (TNR) (only for model data): TNR serves as a measure of uncertainty within the ensemble of climate change projections. It is defined as the ratio of the trend, the so-called signal, to the ensemble standard deviation. The strength of the trend is quantified through the division of the trend by the standard deviation of the model ensemble, facilitating the comparison of trends across different indices by eliminating the influence of unit magnitude. The classification of the Trend-to-Noise Ratio (TNR) is based on the works of Rapp (2000) and Land and Büter (2023). The TNR serves as an indicator of confidence in the projected changes: a higher positive or negative TNR classification signifies a higher probability of change (Supplementary S4), as it indicates consensus among all models contributing to the analysis regarding the direction of the trend. Further insights into the TNR can be found in Hennemuth et al. (2013).

3.2.2. Remote sensing indices

To identify and analyse patterns of changing land cover properties, monthly information with a high spatial resolution is necessary. As such a remote sensing dataset did not exist previously in a sufficient spatio-temporal resolution, two remote sensing datasets were combined and harmonized to derive monthly time series of various remote sensing indices. Two of them, namely the Normalized Difference Vegetation Index (NDVI) and the Leaf area index (LAI) (Supplementary S2), are implemented in the SDSS. The NDVI is a normalized difference between red and near infra-red reflectance and gives information on the greenness of vegetation. It ranges between -1 and $+1$ with dense green vegetation having positive values close to 1, while negative values characterize clouds, water, ice, and snow (Supplementary S5a). The NDVI can be utilized for estimating the healthiness of vegetation. The LAI represents the projected foliage area above a given unit area of ground (Watson, 1947) and is critical for understanding light interception by the canopies as it determines the amount of photosynthetically active radiation and consequently vegetation growth (value explanation see Supplementary S5b).

For generating those indices, daily data from AVHRR – with a pixel size of 5.5 km since 1981 – and daily data of MODIS – with a pixel size of 500 m since 2003 – were used as input variables in machine learning (ML) models that iteratively estimate extrapolate the spatially higher resolved MODIS data to time periods before 2003, where only the coarser AVHRR data is available. This extrapolation is grounded in the statistical relationship assessed during the temporal overlap of the datasets. All data (pre-)processing as well as the ML modelling was carried out in the Python programming language on a high-performance computing server environment. For preparation and pre-processing, the Nearest Neighbour method was applied for resampling the MODIS datasets from a horizontal resolution of 500 m to a pixel size of 1 km. For each month of the year, a composite layer (arithmetic mean) was built for the existing data from 2003 to 2022 to ensure that seasonal fluctuations had no influence. XGBoost and Random Forest algorithms were tested as base for the ML models, as both of them are known for their effectiveness in analysing large spatio-temporal datasets.

From the twelve monthly composites, training and testing datasets were created to train the ML models, utilising MODIS data values and the corresponding month as features. The performance of the tested ML models was assessed using accuracy metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R-squared (R^2). Ultimately, only the XGBoost model was retained for further analysis, as it demonstrated superior efficiency compared to the Random Forest model. Utilising the XGBoost model, MODIS-like datasets at a spatial resolution of 1 km were predicted from historical AVHRR data, resulting in monthly raster predictions for the period from 1981 to 2022.

This structured methodology has provided a dataset of unprecedented spatiotemporal resolution, temporal extent, and range of available land surface parameters. It ensures that the values provided in the SDSS are both reliable and informative, facilitating better decision-making in climate research and policy.

4. Technical implementation

While keeping the requirements, ideas, and needs of the participating stakeholders taken from the co-development and co-design phase with surveys and workshops in mind, the implementation of the SDSS aims to create a technically robust and functional web portal grounded in classic client–server architecture, emphasising high reusability, cross-platform responsiveness (smartphones and computers with different operating systems), and ease of maintainability. This approach seeks to establish a foundation for long-term sustainability and an extended service life. The development leverages a wide array of open-source software components and libraries, ensuring flexibility and adaptability in the portal's functionality and agreeing with the international FAIR principles (Wilkinson et al., 2016). According to the stakeholder demands, the SDSS is designed for both English- and French-speaking users, promoting accessibility and inclusivity.

The resulting technical components and used software of the SDSS are summarised in Fig. 2. The technical implementation is structured around a multi-tier architecture that facilitates efficient data management, user interaction, and asynchronous processing. This section outlines the key components of the system, including the frontend web interface, the GeoServer for data hosting, and the R Plumber API for background calculations.

4.1. Frontend / user interface

At the heart of the SDSS frontend are JavaScript, CSS, and HTML, which work together to create a dynamic and interactive user experience. The OpenLayers third-party JavaScript library is the primary component used for creating maps and displaying raster and vector

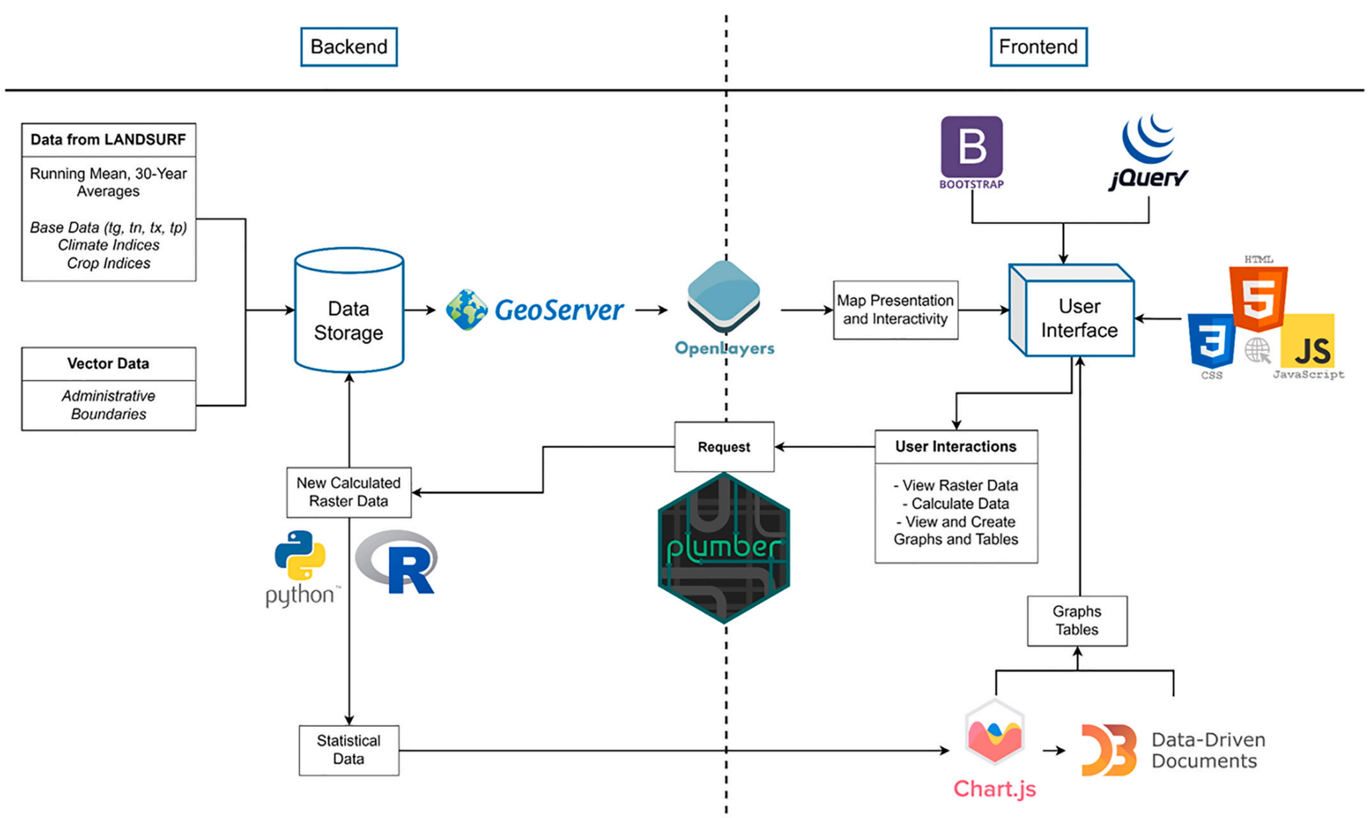

Fig. 2. Overview of the SDSS's components and used software.

layers sourced from Web Map Service (WMS) and Web Feature Service (WFS) in the web portal. Notably, no specific JavaScript framework is employed, allowing for seamless integration of OpenLayers and other third-party libraries. This flexibility enables continuous modifications and enhancements.

The user interface is built using the open source front-end development tool Bootstrap, which provides a responsive design framework for the creation of websites and web apps to ensure best cross-platform performance either using smaller devices like smartphones or devices with bigger screens (e.g. laptop). jQuery is utilised to simplify JavaScript interactions. Additionally, various third-party libraries are incorporated to enhance functionality and streamline coding processes. Users can navigate through a decision tree-like menu to select from a range of data types, including climate, crop, and remote sensing indicators. Upon selecting an indicator for a specific time step, the corresponding WMS is retrieved from the GeoServer and visualised on the map using OpenLayers.

The system also offers the capability to download any dataset as GeoTIFF or netCDF data from the raw data storage. Users can analyse the currently visible dataset or indicator by creating a time series or trend line. To do this, they must select a polygon (representing a predefined administrative boundary) or a point (by clicking on the map) for which the chart will be generated. A request containing all relevant information for the API – such as the dataset, selected region or point, and plot type – is then sent to the R Plumber API (Schloerke & Allen, 2024). The API calculates statistics (e.g., mean values) for each year of the selected region and returns the results as an array. The ChartJS library is employed to create various interactive charts from the returned data, enhancing the user's ability to visualise trends and patterns. Created charts are freely available and can be downloaded by the users, without any registration. Results of the conducted plot or regional analysis are presented in the mapview, by interactive charts and are directly usable through print-ready figures, that the system provides.

4.2. API environment

The R Plumber API plays a crucial role in the SDSS by extracting annual averages for a selected region or point from the raw data for each year within a specified time span, e.g., 1981–2010 for recent data and 1981–2100 for climate model data. Built on the R Plumber library, the API allows for the definition of endpoints where data can be posted and processed.

The entire API environment is set up within a Docker container that runs a nginx web server, ensuring that the API operates continuously and reliably. The API includes different functions tailored to the type of data being analysed—such as climate, drought, crop, or remote sensing indicators—since each data type is structured differently. The API accesses the same raw data repository as the frontend web portal, ensuring consistency and coherence in data handling. Upon processing, the API returns an array of data to the frontend web interface for further analysis and visualisation.

4.3. Development environment and Versions

The SDSS is developed within a robust environment that ensures compatibility and performance. The basis of the system is built on an Ubuntu environment (version 20.04.6). This environment supports the various technologies and software components used in the SDSS, providing a stable platform for development and deployment. By integrating these components, the SDSS provides a comprehensive and efficient platform for climate and land use data analysis and visualisation. The architecture not only supports user interaction but also ensures that data processing and management are handled effectively, paving the way for informed decision-making in climate services. At the landing page the user is welcomed with the selection of language preferences and the option to use an interactive tutorial to get started with the SDSS. At any time users have access to the documentation and help section of the system, where data selection, concentration scenario, preprocessing, and scientific details are findable and described in a plain language.

The design like colormaps, legends, available indices, and documentation was constantly updated with inputs from the project members and stakeholders. The final version of the web portal is currently hosted at https://landsurf.geo.uni-halle.de/ and the code of the DSS web portal is freely available (König et al. 2024) which is also true for all data displayed there (Ziegler et al. 2024b).

5. Demonstration cases

The following two fictional concept studies demonstrate the functionality, usability, and benefits for stakeholders of the created SDSS:

5.1. Concept study I – Farmer: Impact of climate change on irrigation needs in a district in Burkina Faso

This first concept study examines the usage of the SDSS by a farmer in Burkina Faso to analyse the NDVI and irrigation water requirements for millet cultivation. The virtual backstory of this case study is summarized in Supplementary S6. The agricultural sector in Burkina Faso faces significant challenges due to climate variability and change. Understanding the relationship between vegetation indices and irrigation requirements is crucial for optimising water use in crop production. This fictional study illustrates how a farmer employs the SDSS to assess historical NDVI data (1981–2021) and projected future irrigation needs based on the climate scenarios RCP2.6 and RCP8.5.

Initially, the farmer accesses the SDSS to evaluate the NDVI for his fields over a historical period. He selects the data category "Remote Sensing Indicators" and visualises the NDVI on a map (Fig. 3a). By clicking on the pixel corresponding to his field's coordinates (lon -1.416° / lat 11.723°), he retrieves a monthly time series of NDVI values from 1982 to 2021, revealing inner- and interannual fluctuations in vegetation greenness (Fig. 3b). Note that missing values are not interpolated in the time series for reasons of transparency.

Subsequently, the farmer examines the "Irrigation Water Requirement" indicator using ERA5-Land observations for the growth phases of millet. To gain a broader perspective, he expands his analysis to the entire region of Centre-Sud Bazega in Burkina Faso (Fig. 4). He notes an increase of irrigation demand over the years 1981–2010 mainly during the crop development stage (CDS); the latter two (MSS – Mid-Season Stage and LSS – Late Season Stage) remain constant. The farmer brings these findings in line with his knowledge of local characteristics, e.g., related to soil or the availability of groundwater, to enhance his understanding of crop growth dynamics over past decades.

The farmer is also interested in the potential impact of future climate change on his irrigation needs. Therefore, in the next step he selects the "Projection" data type, opting for the "Difference" projection type and "Regional Climate Model" for the highest spatial resolution. He compares the growth phases under the available concentration scenarios: RCP2.6 and RCP8.5. The results in Fig. 5 reveal that under the RCP2.6 scenario, the two early stages, IS and CDS, are projected to reach a maximum increase of $+0.35$ and $+0.7$ mm/day by 2055, respectively. The MSS shows a positive trend as well. The irrigation requirements show a peak after the middle of the 21st century which, however, requires adaptation measures. In contrast, under RCP8.5 all four growth phases show a strongly increasing trend exceeding $+1$ mm/day already around 2050 while especially CDS and MSS can reach an enhanced irrigation requirement of $+2$ mm/day by the end of the century compared with present-day.

Having these strong changes in mind, the farmer utilises the comparative analysis of crops to evaluate the implications of cultivating short versus long millet varieties (Fig. 6a). He concludes that there is small difference in irrigation requirements between the two lengths. The

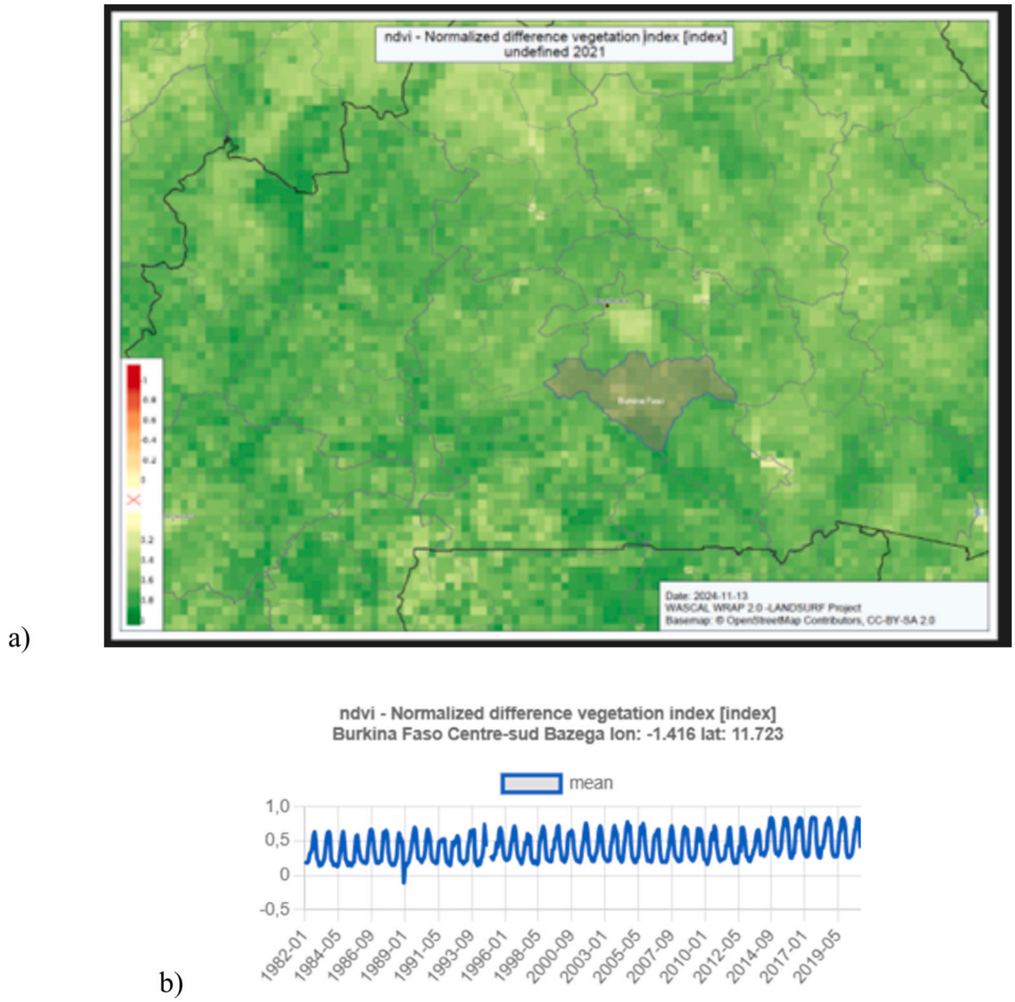

Fig. 3. Map for August 2021 (a) and time series (1982–2020) (b) of absolute values of NDVI (interpretation for this value see Supplementary S5a) for the district Centre-sud Bazega in Burkina Faso.

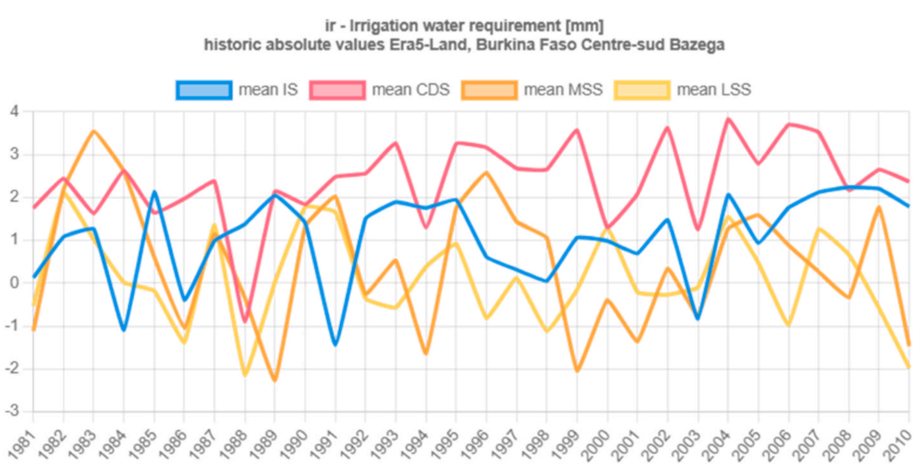

Fig. 4. Time series (1981–2010) of absolute values of irrigation water requirement (ir in mm/day averaged over the indicated region) for four growing stages (IS – Initial Stage, CDS – Crop Development Stage, MSS – Mid Season Stage, and LSS – Late Season Stage) using ERA5-Land for the district Centre-sud Bazega in Burkina Faso.

change signal clearly depends on the RCP scenario. Thus, the crop with the shorter growing season might be preferred from this point of view since the time over which it has to be irrigated is shorter and, consequently, less water is needed. With this knowledge, the question arises whether other crops might have a lower irrigation requirement than millet. Hence, he selects the class of wheat, oat, and barley together with sorghum and two types of maize (sweet, grain) during CDS, the stage affected by the overall strongest increases (Fig. 6b). It turns out that the

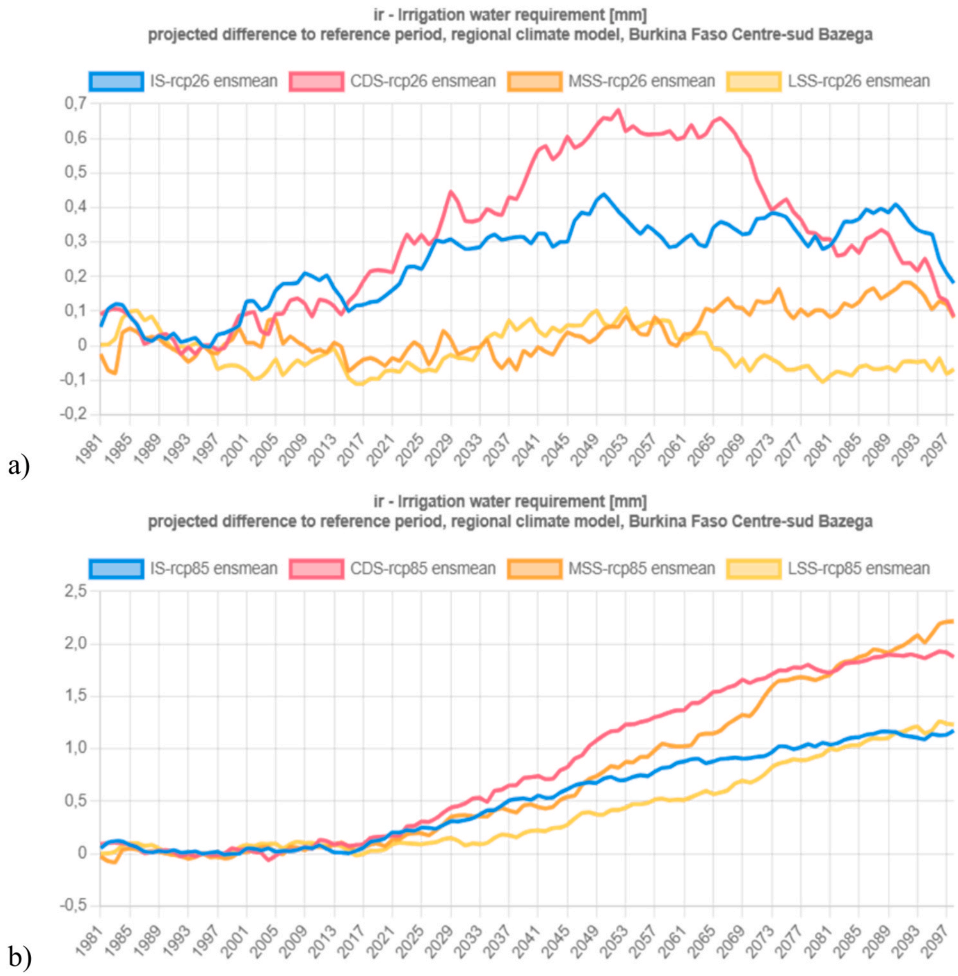

Fig. 5. Time series (1981–2100) of differences in irrigation water requirement (ir in mm/day averaged over the indicated region) for four growing stages (IS, CDS, MSS, and LSS) for RCP2.6 (a) and RCP8.5 (b) using the RCM ensemble mean (ensmean) for the district Centre-sud Bazega in Burkina Faso. Note the different scaling of the y-axis.

respective crop does not play the major role since the irrigation requirements show similar increases of up to +1.2 mm/day at the end of the century. It is slightly larger for maize grain compared with the other crops.

This concept study highlights the importance of utilising a SDSS for informed agricultural management in the face of climate change. By integrating climate model and remote sensing data with local knowledge, farmers can better prepare for the challenges posed by climate variations and ensure sustainable agricultural practices. The farmer's analysis demonstrates significant increases in irrigation needs under future climate scenarios, emphasising the necessity for adaptive strategies in crop selection but mainly on water management practices. In consequence, mitigation and adaptation measures like reservoir constructions and fighting desertification could be realized to keep water from rainfall in natural and artificial storages so that it remains available to meet irrigation requirements.

5.2. Concept study II – Governmental authority (Planner): Impact of climate change on drought events and heat waves in the southern coastal region of West Africa

In a second study, a regional planner at the Ministry of Environment and Sustainable Development in Accra, Ghana, is running an international project that focuses on analysing the impact of climate change on drought events and heat waves in the South Coastal Region of West Africa, which includes Guinea, Sierra Leone, Liberia, Côte d'Ivoire, Ghana, Togo, and Benin. This region is particularly vulnerable to climate variability, with increasing temperatures and changing precipitation patterns threatening agriculture, water resources, and public health. The backstory of this concept study is presented in Supplementary S7. To effectively address these challenges, the planner utilizes the SDSS that can provide comprehensive data analysis and useful information in a fast and efficient way. She assumes that the SDSS will enable her to identify trends, assess risks, and develop targeted strategies to mitigate the impacts of droughts and heatwaves under climate change on regional to local scale and communities. The government is particularly interested in integrating local knowledge and scientific data to create actionable plans that empower communities to adapt to changing conditions.

The planner undertakes a systematic approach to analyse droughts based on the Standardized Precipitation Evaporation Index (SPEI) using ERA5-Land for the historical period (1981–2010). Initially, the SPEI for several countries, focusing on various accumulation periods of 3, 6, 9, and 12 months representing different types of droughts, is selected to create a time series (Fig. 7). Upon examining the resulting plots, the planner observes minor differences across the different accumulation periods averaged over the target countries. Consequently, she opts to utilize the 12-month accumulation interval, as it is more closely associated with the characteristics of long-lasting groundwater droughts and, hence, socioeconomic drought, providing a relevant context for her analysis. In this regard, a drying trend is already detectable.

Following this historical assessment, the user proceeds to evaluate projected absolute values derived from the RCM ensemble under RCP8.5

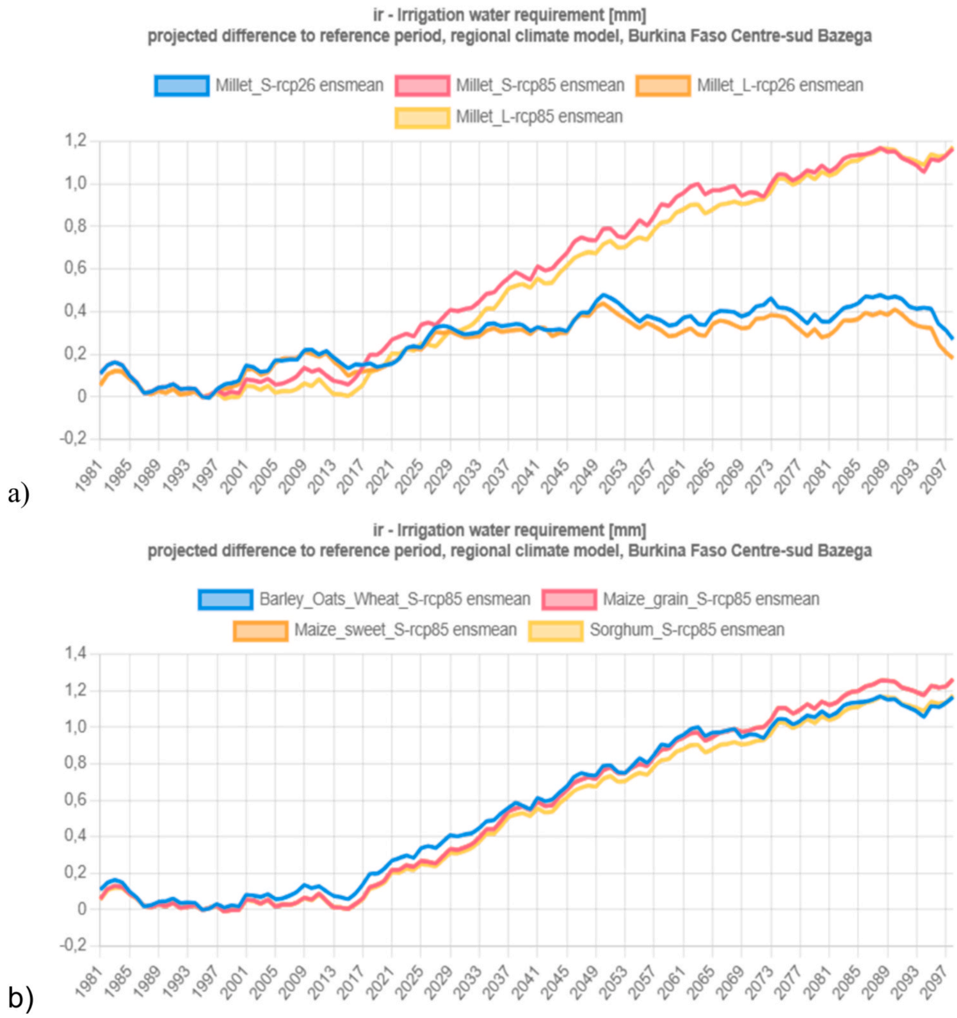

Fig. 6. Time series (1981–2100) of differences in irrigation water requirement (ir in mm/day) for short and long millet for CDS with RCP2.6 and RCP8.5 (a) and for four different crops for short plant lengths and only rcp85 (b) both using the RCM ensemble mean (ensmean) for the district Centre-sud Bazega in Burkina Faso.

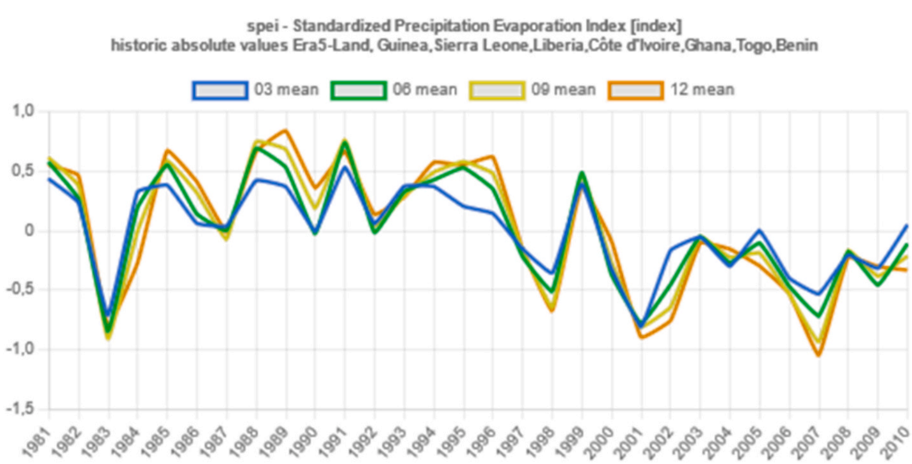

Fig. 7. Time series (1981–2010) of absolute values for SPEI accumulated over 3, 6, 9, and 12 months averaged over the countries Guinea, Sierra Leone, Liberia, Côte d'Ivoire, Ghana, Togo, and Benin.

for the time frame of 2070–2100. To visualize these projections, she generates a map that illustrates the anticipated changes in SPEI, highlighting the risk of severe droughts in southern West Africa (Fig. 8).

Additionally, the planner employs the 'compare scenario' feature to assess the different implications of the two concentration scenarios (Fig. 9). The data reveals that the RCP plays a crucial role for droughts in the area. Using the SPEI classification table from the SDSS documentation (Supplementary S8) it can be concluded that the selected region will face enhanced drought conditions relative to today's climate as pointed out by the ensemble mean and minimum values within the ensemble of

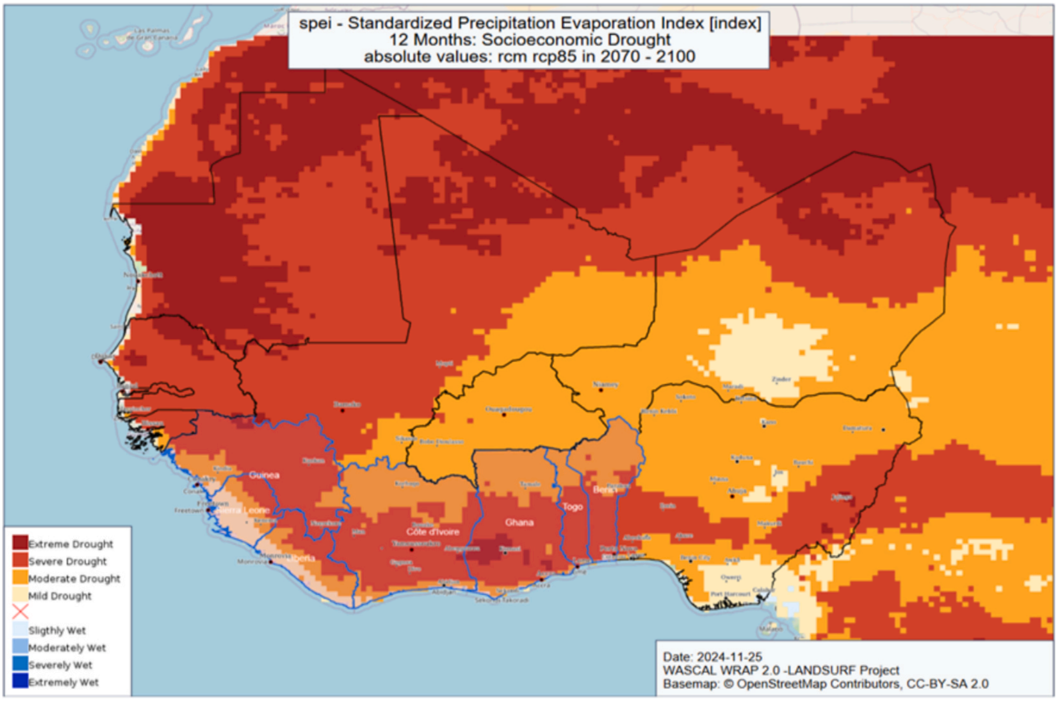

Fig. 8. Map of absolute values for SPEI accumulated over 12 months using the RCM ensemble with RCP8.5 for (2070–2100) (target regions are marked by blue borderlines: Guinea, Sierra Leone, Liberia, Côte d'Ivoire, Ghana, Togo, and Benin).

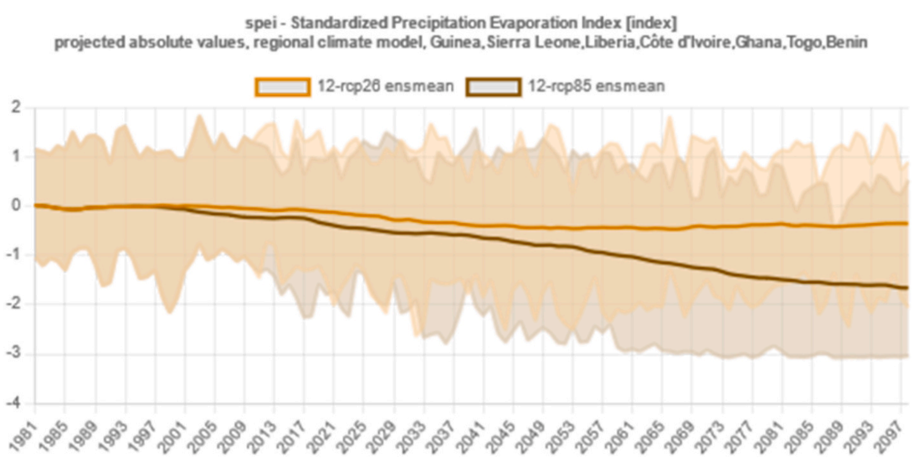

Fig. 9. Time series (1981–2100) of absolute values for SPEI accumulated over 12 months using the RCM ensemble mean under RCP2.6 and RCP8.5 scenario averaged over the countries Guinea, Sierra Leone, Liberia, Côte d'Ivoire, Ghana, Togo, and Benin.

'-3' indicating extreme droughts almost every year towards the end of the century for RCP8.5. In contrast, RCP2.6 implies only slightly drier conditions until the middle of the century stabilizing at a 'normal' level of '+/-1', with ensemble minima of moderate to extreme droughts (−2) in individual years over the entire domain. However, keeping the generated SPEI map in mind (Fig. 8), the conditions will not be homogeneously distributed in space.

These substantial changes in the projected SPEI values highlight the potential impacts of climate change on water availability and drought conditions in the selected regions. In addition, the discrepancy between the concentration scenarios highlights the scope of action arising from an efficient climate mitigation policy. This comprehensive evaluation underscores the importance of considering both historical data and future projections in understanding the dynamics of drought and its socioeconomic implications.

In the context of the planner's inquiry regarding the evolution of extreme temperatures projected by climate models, it is essential to incorporate specific temperature-based indices that provide insight into the potential impacts of climate change on vulnerable populations and agricultural systems. The previously depicted SPEI is based on temperature and precipitation. Therefore, the next index of interest is tx35, indicating the frequency of days when the daily maximum temperature exceeds 35 °C. This threshold is particularly critical, as prolonged exposure to such high temperatures poses significant heat stress and risks to human health as well as to agricultural productivity, especially for crops like maize. Further, the heat wave duration index (HWDI) is informative for this analysis since it is widely utilized in health-related analyses due to its percentile-based calculation, adapting to local climatic conditions. This index measures the longest duration of heat waves per year, together with tx35 providing a clearer understanding of the frequency and intensity of extreme heat events over time.

To assess these indices, the planner chooses the RCM ensemble under

RCP8.5, focusing on the period from 2070 to 2100. As a next step, the trend option can be selected. With this, the planner generates maps illustrating the linear trend for the period 2001–2100 of the number of days exceeding the 35 °C threshold and the duration of heat waves, measured in days per decade. The resulting projections indicate that the entire West African region is expected to experience an increasing trend of 10 to 15 additional days per decade for both the tx35 (Fig. 10a) and the HWDI (Fig. 10b). Furthermore, by utilizing the 'Show Significance of Trend' feature, our fictional planner can visualize the uncertainty associated with these changes. The results reveal a highly significant trend, indicating that all models consistently project an increase in the frequency and duration of heat days and waves which clearly exceeds today's standard deviation (Fig. 10, right panels). This consensus among the models underscores the urgency of addressing the implications of rising temperatures on public health and agricultural resilience in the face of climate change. However, there are variables like the maximal precipitation amount on one day (RX1day) that do not show such homogenous trends (Supplementary S9). The trend shows a spatially separated pattern: a positive trend in the Northwest and a negative one in the Southeast. The time series of the absolute value of RX1day exhibits a large model spread and both RCP scenarios differ considerably (Supplementary S10). Consequently, the resulting TNR pattern of rainfall extremes shows only some areas with significant trends and even less areas with robust trends which is in general contrast to the temperature indices.

6. Discussion and summary

This study describes the motivation behind the development of the SDSS, the participative approach by including stakeholder needs and feedback as well as the preparation of data and calculation of a broad range of indices being relevant for and in use in West Africa's agricultural sector. The accessibility, flexibility, and usability of the SDSS are demonstrated by two concept studies that underline the great potential for numerous stakeholders from different sectors. It gives deeper insights into climate change impact in their respective fields at various spatial scales or administrative levels.

The SDSS implies various benefits for stakeholders. In detail, data at the grid point level as well as for different administrative areas from the country to the district level can be accessed and analysed easily by the user. One or multiple areas can be selected and compared. The information of interest can either be plotted as a map to underline spatial heterogeneities and variations or as time series for the temporal variability and trend. If multiple areas are selected the SDSS automatically calculates the mean of the selected area for the time series figure. Beside absolute values and differences, we also provide estimations of uncertainty by showing ensemble means within the respective ensemble spread, reflecting the potential future pathways of climate until the end of the 21st century. A further uncertainty estimation is delivered by the inclusion of RCM and GCM ensembles. We focus on statistically significant trends and the TNR as a measure of how strong the trend is in relation to the standard deviation of the reference period. These methods make the information provided by the SDSS valuable to stakeholders as well as to students or researchers in a variety of disciplines.

To further support the user, we also provide three different base layers (OSM, ESRI Topographic Base, and ESRI Satellite) for the map display (e.g., Fig. 10a and b). This feature is helpful for specific use cases and orientations especially because the transparency and layer order of the data maps can be selected via a slider and the drag-and-drop method which simplifies the comparison of different time slices or maps. Another advantage of our SDSS is the automatic usage of running means. All climate data is already prepared in a scientific way that provides ready-to-use information. For non-scientific users this option reduces the potential of mistakes when being obliged to perform their own postprocessing of data and prevents misinterpretation of the provided data. For the scientific community we described the preparation process in the documentation and also provide the raw data, if another

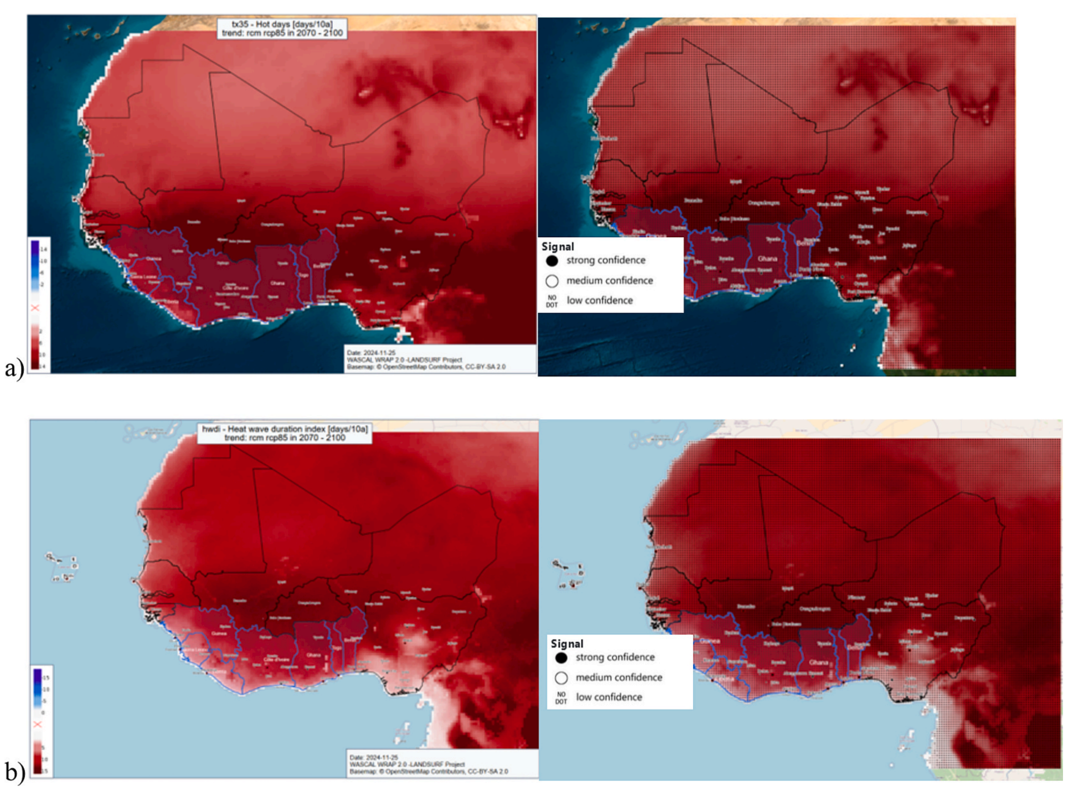

Fig. 10. Trend per decade for tx35 (a) and HDWI (b) using the RCM ensemble mean with RCP8.5 (left) and the corresponding TNR indicated by hatching (right) (target regions are marked by blue borderlines: Guinea, Sierra Leone, Liberia, Côte d'Ivoire, Ghana, Togo, and Benin).

proceeding should be preferred.

The plots generated within the SDSS can be downloaded to be presented and distributed by the respective users. More advanced users can further download time series data in csv-format and maps in GeoTiff and NetCDF to perform their own analyses without downloading and processing large data volumes from climate model simulations. The broad range of available indicators and crops makes the SDSS relevant for agricultural stakeholders at every level. Moreover, the indicator selection might also attract stakeholders beyond agriculture, e.g., from regional development, water administrations, migration offices, or educational institutions.

The format of the SDSS is advantageous compared with some existing data portals since the web-based approach enables an easy access which does not require any accounts, additional or even advanced skills, nor software to derive detailed and science-based information on climate and land use change. However, this web-based approach also comes with a small weakness as the user has to be online at least initially to access the portal and data but can download the desired information for further offline usage. Presenting the information in this way reduces accessibility barriers and is entirely free of charge. To provide the information to as many people as possible, the entire SDSS as well as its non-scientific documentation is available in English and French.

Finally, the code of the SDSS is freely available (König et al. 2024) which is also true for the data shown in the system (Ziegler et al. 2024b) and the intermediate data where the original ones are processed (Ziegler et al. 2024a).

In summary, we aimed at combining the strengths from previous SDSS approaches dedicated to climate impact research in Africa (cf. Section 1). Stress was laid on a stakeholder involvement prior to designing the SDSS, a high spatial resolution, a wide range of climate indicators of high practical relevance, a broad spectrum of statistical data processing, a free download of raw data and charts, and a barrier-free technical implementation in terms of the usability, interpretability, language and hardware compatibility. Another advantage compared with other systems is the easy-to-use comparison function among scenarios, indicators, regions, crops and growing stages. Our SDSS will be continuously maintained beyond the project's funding period. In the meantime, it is also available via various institutional websites in West Africa.

There is still a large potential of improvement, depending on future funding and availability of new datasets. While using standard methods for the preparation of the remote sensing indices, we have detected some limitations (e.g., missing values, negative values, or 'jumps' due to the satellite input data) of those methods. Therefore, especially for these indices there is the need and potential for improvements, e.g. using newly developed methods like Deep Learning modules to get NDVI values from weather data (Janetzky et al., 2024). Further, the next generation of RCM simulations will expand to the convection-permitting scale, allowing an even better representation of local weather extremes. The spectrum of indicators is indeed of practical relevance but still confined to climatic and crop information. Socio-economic indicators like income, operating expenses for seeds, fertilizers, and pesticides as well as investments in irrigation systems or new cropping systems may enhance the user potential of the SDSS. The same is true for human health issues due to heat stress, malnutrition, enhanced UV exposure, and air pollution during dry episodes. Finally, the statistical toolbox of the SDSS can be extended, e.g., by a correlation analysis between climate, vegetation and crop indices or multiple regression models, enabling students and scientists to detect cause-and-effect chains between climate change and affected sectors in Africa.

"During the preparation of this work the author(s) used ChatGPT in order to embellish and fill up the backstories of the persons from the two concept studies. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication."

CRediT authorship contribution statement

Katrin Ziegler: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Daniel Abel:** Writing – review & editing, Writing – original draft, Visualization, Validation, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Lorenz König:** Visualization, Software, Methodology. **Torsten Weber:** Writing – review & editing, Visualization, Funding acquisition, Formal analysis. **Insa Otte:** Writing – review & editing, Formal analysis, Data curation. **Mike Teucher:** Writing – review & editing. **Christopher Conrad:** Writing – review & editing, Supervision, Resources, Funding acquisition, Conceptualization. **Michael Thiel:** Writing – review & editing, Funding acquisition. **Imoleayo Ezekiel Gbode:** Writing – review & editing. **Vincent Olanrewaju Ajayi:** Writing – review & editing. **Amadou Coulibaly:** Writing – review & editing. **Seydou B. Traoré:** Writing – review & editing. **Benewinde Jean-Bosco Zoungrana:** Writing – review & editing. **Heiko Paeth:** Writing – review & editing, Supervision, Resources, Project administration, Conceptualization.

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.

Acknowledgements

We thank the World Climate Research Programme (WCRP) for supporting the CMIP and CORDEX initiatives, providing the analyzed global and regional climate model projections, the ECMWF for providing the ERA5-Land datasets, the US Geological Survey (USGS) for making the CHIRPS data available, and also EROS and NASA for the AVHRR and MODIS data. We also would like to thank the Deutsches Klimarechenzentrum (DKRZ) for granting computing time and storage under the project ID bb1340 necessary to create our indicator data.

Funding

This study has been conducted in the framework of the research project WASCAL WRAP2.0: LANDSURF (grant numbers 01LG2080A-C) funded by the German Federal Ministry for Education and Research (BMBF) via the project manager at the German Aerospace Center (DLR Projektträger).

Data Availability.

All datasets analysed are publicly available through the ECMWF, CORDEX-Africa and CMIP websites. The SDSS is open access under the URL https://landsurf.geo.uni-halle.de. The underlying code and data have been published by König et al. (2024) and Ziegler et al. (2024a, b), respectively.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cliser.2025.100585.

Data availability

Data availability of this research see corresponding paragraph in the manuscript.

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