Development of a climate and water availability indices app to support decision-making across South African water management areas

Final report to the

Water Research Commission

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Executive summary

Rationale

South African agriculture operates within a context of high climate variability, increasing weather and climate extremes, and water scarcity. Crop and livestock production are strongly influenced by the timing, intensity, and variability of rainfall, temperature, and other weather- and climate-related extremes, and the availability of water within the landscape. Weather- and climate-related risks such as heavy rainfall events, drought, heat stress, and extreme cold events directly affect crop yields, livestock health and productivity, grazing availability, frost risk, and irrigation demand. As a result, agricultural decision-making, from day-to-day operational choices to seasonal planning and longer-term risk management, is highly dependent on access to reliable, timely, and relevant weather and climate information.

In recent decades, these challenges have intensified as climate variability and climate change have increased the frequency and severity of weather and climate extremes. Rising temperatures, shifting rainfall characteristics, and more frequent compound events place additional pressure on already vulnerable farming systems, particularly in semi-arid and water-limited regions, such as South Africa. For farmers, planners, and agricultural advisory services, the challenge is not only that weather- and climate-related risks are increasing, but that uncertainty around these risks complicates decision-making and limits the effectiveness of proactive adaptation strategies.

Although South Africa has access to a wide range of high-quality weather, climate, and hydrological datasets, including long-term station records, satellite-derived products, and reanalysis datasets, these data are rarely accessible to agricultural users in a form that directly supports interpretation and decision-making. Raw meteorological and hydrological datasets typically require specialised software, technical expertise, and substantial processing before they can be meaningfully interpreted. These barriers limit uptake by farmers, extension officers, planners, and local decision-makers, resulting in valuable data remaining underutilised. If this gap between data availability and practical use is not addressed, climate and water risks are likely to continue being managed reactively, undermining agricultural resilience and adaptive capacity.

One widely recognised approach to addressing this challenge is the use of pre-derived weather- and climate-based indices. Such indices distil complex daily datasets into targeted, interpretable metrics that describe aspects of weather and climate directly relevant to agricultural impacts and management decisions, such as rainfall frequency, heat stress conditions, frost occurrence, or short-term rainfall deficits. When appropriately selected and clearly communicated, indices provide a practical bridge between climate data and agricultural decision-making. However, the computation, evaluation, and interpretation of indices still require methodological choices, data handling skills, and contextual understanding that are not always available outside specialist or research environments.

In parallel with climatic conditions, water availability plays a critical role in shaping agricultural risk, particularly in irrigated systems and in catchments where competition for water resources is high. Weather and climate signals gain additional practical relevance when considered alongside their implications for surface water, groundwater, and overall water availability. Integrating weather and climate indices with selected water availability indicators, therefore, provides a more complete and decision-relevant picture of risk, linking atmospheric conditions to agricultural production and water-resource pressures.

Despite the clear value of indices and integrated climate-water information, existing weather and climate service (WCS) platforms in South Africa tend to be limited in scope or focus. Many rely primarily on station-based data, emphasise monthly or seasonal summaries, or treat climate and hydrology in isolation. Such approaches can smooth out short-term variability and extremes that are critical for agriculture and limit usefulness for near-term and operational decision-making. There is, therefore, a clear need for an accessible, agriculture-focused platform that operationalises weather- and climate-based indices alongside water availability indicators and delivers this information in a form that is spatially explicit, timely, and interpretable.

Against this backdrop, the Weather Risk app was conceived as a response to a clearly identified scientific and practical gap. The project was motivated by the need to both improve access to actionable weather and water availability information for agriculture and to ensure that the indices underpinning such information are scientifically robust, contextually appropriate, and transparent in their limitations. Addressing this need required more than the development of a user-facing application; it necessitated a structured review of climate and water availability indices and climate service principles, applied evaluation of gridded datasets and indices through case studies, and an operational implementation informed by stakeholder engagement.

The challenge of managing agricultural decision-making under climate change, increasing climate variability, and limited access to integrated weather and water availability information is critical within the broader context of national water security. Agriculture remains one of the largest water-using sectors in South Africa, and climate change and climate-driven variability in water availability place increasing pressure on already stressed surface and groundwater systems. Improving access to integrated weather- and water-related information directly supports informed planning, risk reduction, and sustainable resource use, and aligns strongly with the Water Research Commission's (WRC's) strategic priorities related to water security, climate adaptation, and resilience.

Against this background, this project was undertaken to bridge the gap between weather, climate, and water availability data availability and their effective use in agricultural decision-making. By integrating a targeted review, applied evaluation, stakeholder engagement, and operational delivery through a web-based platform, the project responds to pressing climate and water challenges facing South African agriculture and provides a foundation for strengthening WCSs in support of agricultural resilience.

Objectives

Main aim of the study

The main aim of the project was to support agricultural decision-making in South Africa by identifying, testing, and operationalising selected weather-, climate-, and water availability indices through the development of an accessible, web-based information platform (namely, the Weather Risk app).

Specific objectives

1. To undertake a targeted review of existing climate databank applications, climate service principles, and commonly used weather- and climate-based indices alongside water availability

indices relevant to climate-sensitive activities in South Africa (e.g., agriculture and water resource management), with a primary focus on rainfall and temperature variables.

2. To evaluate selected gridded climate datasets and undertake illustrative case studies demonstrating the computation and application of rainfall- and temperature-based climate indices, including both indices linked to agricultural indicators (such as crop production and livestock numbers) and indices used to characterise climate extremes (e.g., cold events), to demonstrate potential applications and limitations.

3. To develop and implement a web-based application (i.e., the Weather Risk app) that provides spatially explicit weather-based indices, alongside water availability indicators, to support agricultural decision-making across South Africa.

Results or products

The outputs included a defensible review of existing climate databank and web-based applications, climate service principles, and selected climate-, and water availability indices applied over South Africa; applied case studies demonstrating different applications of indices, including their use for general interpretation, their linkage with agricultural productivity statistics, and the evaluation of gridded datasets for index calculation; stakeholder-derived insights into national weather and climate information needs and the challenges associated with accessing and using such information; structured feedback from questionnaire-based evaluation of the Weather Risk app, demonstrating practical approaches for assessing the usability, interpretation, and effectiveness of a developed WCS; and a publicly accessible web-based platform delivering operational weather and water availability indices for agricultural use, known as the Weather Risk app.

Achievement of objectives

All project objectives were achieved. The review of climate databank applications, climate service principles, and relevant climate- and water availability indices was completed as planned, providing a robust foundation for index selection and platform design. Selected gridded datasets and indices were evaluated through illustrative case studies, demonstrating different applications of indices, their relevance in agricultural contexts, and the evaluation of gridded data for index calculation.

Stakeholder engagement formed a central component of the project and contributed directly to achieving the objectives. An early-stage, national questionnaire was used to assess weather and climate information needs, access, use, and constraints across South Africa, informing index prioritisation and platform requirements for the Weather Risk app. A subsequent stakeholder engagement and user-testing phase focused on evaluating the Weather Risk app itself, providing structured feedback on usability, interpretation, and functionality, and demonstrating practical approaches for assessing the effectiveness of a developed WCS. Insights from both phases were incorporated into the design and content of the platform, with additional insights continuing to inform ongoing refinement and enhancement.

While not all indices included in the operational platform were evaluated in detail within the project timeframe, this was a deliberate and transparent design choice. The project prioritised demonstrating operational feasibility, stakeholder relevance, and usability, while establishing a foundation for continued evaluation, refinement, and expansion of indices beyond the project lifecycle.

Location of the project

The project was implemented at a national scale, with a primary focus on South Africa.

Methodology

The project followed an integrated methodology combining targeted literature reviews, applied index application and data evaluation, stakeholder engagement, and operational system development. A structured review of climate databank and web-based applications, climate service principles, and relevant indices contributed to informed index selection and platform design of the Weather Risk app. Selected gridded climate datasets were evaluated, and indices were computed and applied through illustrative case studies, including demonstrations of index values for interpreting climatic conditions, exploration of linkages with agricultural productivity statistics, and evaluation of gridded data suitability for index calculation. Stakeholder engagement included an initial questionnaire to identify national weather and climate information needs, access, and constraints, followed by user-testing and questionnaire-based feedback to evaluate the Weather Risk site and guide ongoing refinement. The Weather Risk app was developed and implemented through an iterative, user-informed process.

Results

The project delivered a publicly accessible, web-based Weather Risk app that operationalises a suite of weather- and water availability indices relevant to agriculture. The platform integrates observed and forecast weather data with selected water availability indicators, providing spatially explicit and regularly updated information across South Africa. Findings from the structured literature review informed both the selection of indices and the design of the platform, ensuring alignment with established climate service principles and existing best practices in climate databank and web-based application development. Applied case studies demonstrated different applications of indices, including their use for general interpretation, exploration of linkages with agricultural productivity statistics, and evaluation of gridded datasets for index calculation. Stakeholder engagement and questionnaire-based evaluation highlighted strong demand for accessible and interpretable weather and climate information and provided feedback that informed both the design and ongoing refinement of the platform.

Short summary of key results

- Weather- and climate-based indices provide clear added value for agricultural decision-making

The results show that indices translate complex weather and climate data into interpretable information that supports agricultural risk awareness and practical decision-making beyond what raw variables can provide.

- Different applications of indices support different decision needs

Indices were shown to be useful for general interpretation of climatic conditions, for exploring linkages with agricultural productivity indicators, and for evaluating the suitability of gridded datasets for operational use.

- Integrating weather and water availability information improves relevance for agriculture.

Presenting weather indices alongside selected water availability indicators through the Weather Risk app can enable users to better contextualise conditions in terms of irrigation demand, grazing pressure, and resource availability.

- Stakeholder engagement confirmed both demand for and barriers to using weather and climate information.

Results highlight strong interest in accessible, short-term, and spatially explicit information, while also identifying challenges related to access, interpretation, and usability that need to be addressed through WCS design.

- Questionnaire-based evaluation demonstrated practical approaches to assessing WCSs.

Feedback on the Weather Risk app illustrates how structured user engagement can be used to evaluate usability, interpretation, and perceived value, and to guide ongoing WCS refinement.

Use of results and beneficiaries

The results of this project are intended to support farmers, extension officers, researchers, planners, and policymakers involved in agricultural and water-related decision-making. The Weather Risk app and associated findings can be used to support situational awareness, retrospective assessment of conditions, and near-term planning, while also informing the development, evaluation, and refinement of future WCSs.

Discussion

The findings demonstrate that weather and climate indices provide more actionable and decision-relevant information than raw weather and climate data alone, particularly when applied across different timescales and framed around agriculturally meaningful thresholds, accumulation periods, and impact-oriented questions. The applied case studies illustrate how indices can be used not only for general interpretation of conditions, but also to explore linkages with agricultural productivity and to assess the suitability of underlying gridded datasets for operational use. The work further highlights the importance of transparency regarding data sources, uncertainty, and appropriate interpretation. Feedback from stakeholder engagement and platform evaluation underscores the need for accessible, clearly explained, and integrated weather-water information. By combining scientific robustness with user-centred design and iterative evaluation, the Weather Risk app is positioned as an evolving operational WCS rather than a static research output.

Conclusions and recommendations for further research

This project shows that weather- and climate-based indices can be effectively operationalised within a user-focused WCS to support agricultural resilience and water-informed decision-making. By translating complex weather and water availability data into accessible, spatially explicit indices, the Weather Risk app can provide users with a practical means to better interpret conditions relevant to agricultural planning, risk awareness, and resource management, with additional decision value anticipated as advisory messaging is further developed and implemented. A key message for users is that weather and climate information are most useful when it is framed around agriculturally meaningful indices, transparently communicated, and delivered through an operational platform that evolves in response to user needs.

Building on these outcomes, several priorities for future WRC-supported research are identified. Further work is needed to strengthen the understanding of relationships between weather- and climate-based indices and agricultural responses across South Africa, spanning different production systems, regions, and timescales, including compound and interacting risks. Continued evaluation of gridded datasets is required to build on existing validation efforts and to assess the suitability of new products as they become available, particularly for indices characterising extremes. Targeted support for strengthening forecasting capabilities within the Agricultural Research Council, including improvements in forecast resolution, forcing data options, and overall forecast quality, alongside the development and evaluation of forecast-based indices, represents a key opportunity to enhance anticipatory decision-making through the Weather Risk app. In addition, further research exploring additional water availability indices and strengthening the links between weather, climate, and water availability information would enhance relevance for irrigated agriculture and water resource management. Finally, future work focused on evaluating the on-the-ground use and impact of the Weather Risk app would provide critical evidence of value, inform targeted refinement, and support continued investment in operational WCSs for agriculture in South Africa.

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List of Abbreviations and Acronyms

ADEWS	Agricultural Drought Early Warning System
AgERA5	Agronomic ERA5
ARC	Agricultural Research Council
ARW	Advanced Research WRF
CUAHSI	Consortium of Universities for the Advancement of Hydrologic Science, Inc.
CDS	Climate Data Store
CHIRPS	Climate Hazards Group InfraRed Precipitation with Station data
CPC	Climate Prediction Centre
CRU	Climate Research Unit
CSAG	Climate System Analysis Group
DoA	Department of Agriculture
DWS	Department of Water and Sanitation
ECMWF	European Centre for Medium-Range Weather Forecasts
ELTEs	Extreme Low Temperature Events
ENSO	El Niño-Southern Oscillation
ERA5	ECMWF Reanalysis v5
ERA5-Land	ECMWF Reanalysis v5 for the land
ETa	Actual Evapotranspiration
FAO WaPOR	Food and Agriculture Organization Water Productivity through Open access of Remotely sensed derived data
GEE	Google Earth Engine
GFS	Global Forecast System
HI	Heat Index
IPCC	International Panel on Climate Change
MODIS	Moderate Resolution Imaging Spectroradiometer
NOAA	National Oceanic and Atmospheric Administration
NCEP	National Centers for Environmental Prediction
PET	Potential Evapotranspiration
R10mm	Heavy rainfall days
R20mm	Very heavy rainfall days
SAEON	South African Environmental Observation Network
SANSA	South African National Space Agency
SARVA	South African Risk and Vulnerability Atlas
SAST	South African Standard Time
SAWS	South African Weather Service
SRA	Standardised Rainfall Anomaly
SSL	Secure Sockets Layer
THI	Temperature-Humidity Index
Tn	Minimum temperature
Tx	Maximum temperature
UTC	Coordinated Universal Time
WCS	Weather and climate service
WMA	Water Management Area
WRC	Water Research Commission
WRF	Weather Research and Forecasting

Chapter 1: Introduction

1.1 Research background and motivation

Agriculture in South Africa is inherently weather- and climate-sensitive (Malherbe et al., 2025; Simanjuntak et al., 2023). Both crop and livestock production are strongly influenced by the timing, intensity, and variability of rainfall, temperature extremes, and the availability of water within the landscape (Zinyengere et al., 2013; Maluleke & Mokwena, 2017; Bradshaw et al., 2022; Zhou et al., 2022; Simanjuntak et al., 2023). These hydroclimatic conditions directly affect planting and harvesting opportunities, grazing capacity, livestock heat stress, frost risk, irrigation demand, and overall farm productivity (Zinyengere et al., 2013; Maluleke & Mokwena, 2017; Bradshaw et al., 2022; Zhou et al., 2022; Simanjuntak et al., 2023). Consequently, agricultural decision-making, from daily operational choices to seasonal planning and longer-term risk management, depends critically on access to reliable, timely, and relevant weather and climate information (Hansen et al., 2019; Vaughan et al., 2019; Lumbroso et al., 2024; Moeletsi & Tsubo, 2024).

In recent decades, the agricultural sector has faced increasing pressure from climate variability and anthropogenically induced climate change (Yuan et al., 2024). Observed trends across South Africa indicate rising temperatures (van der Walt & Fitchett, 2020b, 2021), shifts in rainfall characteristics (Kruger & Nxumalo, 2017b; Roffe et al., 2021), and an increased frequency and intensity of weather and climate extremes such as droughts, floods, and heatwaves occurring alone or in a compound manner (McBride et al., 2022; Meque et al., 2022; Mbokodo et al., 2023; Chivangulula et al., 2025). These changes compound existing vulnerabilities in an already water-scarce country and place additional stress on agricultural systems and water resources (Yuan et al., 2024). For farmers and agricultural planners, the challenge is not only that weather-related risks are increasing, but that the uncertainty surrounding these risks complicates decision-making, particularly in semi-arid and highly variable regions (Myeni et al., 2024).

Although South Africa has a strong foundation of weather and climate data, including long-term station records (Moeletsi et al., 2022), satellite-derived products (Du Plessis & Kibii, 2021), and reanalysis datasets (Roffe & van der Walt, 2023), these data are rarely accessible to agricultural users in a form that directly supports decision-making (Myeni et al., 2024; Myeni & Roffe, 2025). Raw meteorological and hydrological datasets typically require specialised software, technical expertise, and substantial processing before they can be interpreted meaningfully. For many farmers, extension officers, and local decision-makers, these barriers effectively limit the practical use of otherwise valuable information. Consequently, weather and climate data often remain underutilised, even where high-quality datasets are available.

One way of addressing this challenge is through pre-derived datasets of weather- and climate-based indices. These kinds of indices distil complex datasets into targeted metrics that describe specific aspects of weather and climate relevant to impacts and decision-making, such as the number of rain days over a given period, the frequency of very hot days, the occurrence of frost, or short-term rainfall deficits (Zhang et al., 2011). When appropriately selected and clearly communicated, indices provide a powerful means of translating weather and climate information into a form that aligns with agricultural questions and management needs (Zhang et al., 2011). However, the computation and interpretation of such indices still require methodological choices, data handling skills, and contextual understanding that are not always readily available outside research and specialist environments.

In addition to climatic conditions, water availability plays a critical role in shaping agricultural risk, particularly in irrigated systems and in catchments where competition for water resources is high (Liu et al., 2022). Weather and climate signals such as prolonged dry spells or anomalously high rainfall only gain practical relevance when considered alongside their implications for surface water, groundwater, and overall water availability (Liu et al., 2022). Integrating weather and climate indices with selected water availability indicators, therefore, provides a more complete picture of risk, enabling users to contextualise conditions in terms of potential impacts on agricultural production and resource management (Bonetti et al., 2022).

Despite the clear value of indices and integrated climate-water information, existing platforms in South Africa tend to be limited in scope (Lumbroso et al., 2024; see Section 2.3.2). Many applications rely primarily on station-based data and focus on monthly, seasonal, or annual summaries, which can smooth out important short-term variability and extremes that are critical for agriculture (Lumbroso et al., 2024). Others do not routinely incorporate weather and climate indices, or focus narrowly on either climate or hydrology, without providing an integrated perspective (Lumbroso et al., 2024). Moreover, available platforms often prioritise general climatological reporting rather than operational agricultural relevance, limiting their utility for day-to-day and near-term decision-making (Lumbroso et al., 2024).

Against this backdrop, the development of an accessible, agriculture-focused platform that operationalises weather- and climate-based indices represents a critical opportunity to bridge the gap between data availability and practical use. The Weather Risk app was conceived to address this need by providing a centralised, web-based resource that transforms diverse meteorological and hydrological datasets into spatially explicit indices tailored to agricultural decision-making across South Africa. By removing the need for users to access, process, and analyse raw data, the platform lowers technical barriers and supports a wider range of stakeholders, including farmers, extension officers, researchers, and agricultural planners.

The motivation for this project was therefore twofold. First, there was a clear need to support agricultural decision-making under increasing weather and climate risk by improving access to relevant, interpretable, and timely weather and climate information. Second, there was a research need to critically evaluate the datasets and indices that underpin such information, ensuring that they are scientifically robust, contextually appropriate, and transparent in their limitations. Addressing these needs required not only the development of a user-facing application but also a structured assessment of data sources, index formulations, and example applications that demonstrate both value and constraints.

In response to these challenges, the project *Development of a Climate and Water Availability Indices App to Support Decision-Making Across South African Water Management Areas* (project number C2023/2024-01182) was proposed and funded by the Water Research Commission (WRC). The project was led by the Agricultural Research Council (ARC) Agrometeorology Division and supported by the Water Science Division and developers, and outside of the ARC, the project brought together expertise from collaborating institutions, including the University of the Free State, the South African Weather Service (SAWS), and North-West University. Commencing in April 2023 and concluding in March 2026, the project combined applied research with operational implementation.

Central to the project was the recognition that the credibility and usefulness of weather and climate services (WCSs) depend on more than data availability alone. Effective WCSs must be grounded in established WCS frameworks, be responsive to user needs, and clearly communicate uncertainty and limitations. Accordingly, the project undertook a targeted review of existing climate databank applications, WCS principles, and commonly used weather- and climate-based indices (namely, rainfall and temperature indices) relevant to agriculture and water management. This provided a starting foundation for selecting indices that are both scientifically defensible and practically meaningful within the South African agricultural context.

Building on this foundation, the project evaluated selected gridded climate datasets and applied them in illustrative case studies to demonstrate how rainfall- and temperature-based indices can be computed and interpreted. Emphasis was placed on indices linked to agricultural indicators, such as crop production and livestock dynamics, as well as indices used to characterise weather and climate extremes, including cold events. These case studies serve a dual purpose, such that they highlight the potential value of indices for agricultural applications, while also illustrating data limitations, regional differences, and sources of uncertainty that users need to consider.

The culmination of this work is the Weather Risk app itself, which operationalises selected indices within a web-based platform. By providing spatially explicit outputs, daily updates, and intuitive visualisations, the app functions as both a decision-support tool and a weather and climate information resource for agriculture. While the platform is national in scope, its design reflects the diversity of South African farming systems and the need for information that can be interpreted at multiple spatial and temporal scales.

In summary, this project was motivated by the growing need to support agricultural resilience in a changing climate through improved access to actionable weather and climate information. By integrating rigorous data evaluation, applied case studies, and an operational web-based platform, the project advances both the practice of WCSs and their application within the agricultural sector. The research background outlined here provides the context for the project aim and objectives that follow and frames the Weather Risk app as a response to clearly identified scientific and practical challenges in agricultural decision-making across South Africa.

1.2 Aim and Objectives

The main aim of this project was to support agricultural decision-making in South Africa by identifying, testing, and operationalising selected weather-, climate-, and water availability indices through the development of an accessible, web-based weather and water availability information platform (namely, the Weather Risk app).

To achieve this aim, the specific objectives of the project were:

1. To undertake a targeted review of existing climate databank applications, climate service principles, and commonly used weather- and climate-based indices alongside water availability indices relevant to climate-sensitive activities in South Africa (e.g., agriculture and water resource management), with a primary focus on rainfall and temperature variables.
2. To evaluate selected gridded climate datasets and undertake illustrative case studies demonstrating the computation and application of rainfall- and temperature-based climate indices, including both indices linked to agricultural indicators (such as crop production and livestock numbers) and indices used to characterise climate extremes (e.g., cold events), to demonstrate potential applications and limitations.

3. To develop and implement a web-based application (i.e., the Weather Risk app) that provides spatially explicit weather-based indices, alongside water availability indicators, to support agricultural decision-making across South Africa.

1.3 Report Outline

This final project report has been divided into seven chapters, which are structured as follows:

This introductory chapter (i.e., Chapter 1), presenting the research background, motivation, and aim and objectives, is followed by a literature review chapter (Chapter 2) addressing Objective 1 of the research project. This chapter is presented in two parts. Part one presents a review of climate and water availability indices applied in a South African context, while part two presents a review of climate databank apps and WCS principles, both of which are fundamental reviews for the development of the Weather Risk app.

To demonstrate the value of weather and climate indices, Chapter 3 presents the application of weather and climate indices in an agricultural context, while also considering relevant gridded datasets for calculating indices. This chapter addresses Objective 2 of the research project.

The next three chapters contribute to addressing Objective 3 of the research project. Chapter 4 presents the stakeholder engagement activities that informed the development of the Weather Risk app, which included a focus group meeting as well as responses to a questionnaire. Chapter 5 builds on this chapter by providing background to the development of the Weather Risk app. This chapter begins by noting the user-centric design of the app. Next, the input data, and the weather and the water availability indices are presented. This is followed by a discussion of the overall design, development, and functionality of the Weather Risk app, while information on the project's GitHub repository and user guide is presented thereafter. Following this, Chapter 6 presents the stakeholder engagement activity undertaken to test the app, considering the system's functionality and determining how well it meets user expectations, while also gathering feedback to improve the site.

Finally, Chapter 7 presents a synthesis of the research report, and is followed by the References section, listing the literature cited in the report. An Appendices section provides further information on the capacity building and research dissemination undertaken throughout the project.

Chapter 2: Literature review

2.1 Introduction

This chapter addresses the first objective of the project, which comprised two related components. The first was to undertake a targeted review of commonly used weather- and climate-based indices, together with water availability indices, relevant to climate-sensitive activities in South Africa (e.g., agriculture and water resource management), with a primary focus on rainfall and temperature variables. The second was to undertake a review of existing climate databank applications and climate service principles relevant to their operational delivery. In doing so, this objective recognises that the effectiveness of an operational WCS depends not only on the availability of high-quality data, but also on the careful selection, interpretation, and presentation of information that is directly relevant to decision-making contexts(Hansen et al., 2019; Vaughan et al., 2019; Walker, 2020; Moeletsi & Tsubo, 2024).

In addressing the first component of this objective, attention is given to rainfall- and temperature-based indices, which are widely used to summarise complex daily weather and climate data into interpretable measures describing average conditions, variability, and extremes. When appropriately selected, such indices provide information that is closely aligned with climate impacts on crops, livestock, and water resources, thereby offering a practical bridge between climate data and sector-specific decision-making needs. Water availability indices extend this climatic information by describing key components of the surface and subsurface water balance, linking atmospheric conditions to the availability of water resources that underpin many climate-sensitive activities. Accordingly, this chapter first reviews commonly applied rainfall- and temperature-based indices, together with selected water availability indices, that have been used in South African agricultural and water-resource contexts. The review focuses on indices that are applicable at the national scale, can be consistently derived from weather station and gridded datasets, and are suitable for operational monitoring and decision-support applications.

The review of climate and water availability indices presented in this chapter builds directly on a project deliverable completed in December 2023. The structure and core content of that review are retained here to ensure consistency across project outputs and alignment with the approved project scope. Minor refinements have been applied in the final report to clarify definitions, scope, and relevance to operational decision-making, and to strengthen alignment with the current design and functionality of the Weather Risk app. The review is intended to provide a practical, application-oriented inventory of indices, rather than an exhaustive assessment of all indices reported in the literature.

Following the review of indices, this chapter examines existing web-based weather and climate databank applications and key WCS principles relevant to South Africa, both of which were similarly part of the deliverable completed in December 2023. This second component considers aspects such as user-centric design, credibility, usability, and evaluation, and situates the Weather Risk app within the broader landscape of comparable tools. Insights from this review informed the operational design and implementation of the Weather Risk app, ensuring that selected indices are delivered through a platform that is accessible, trustworthy, and responsive to user needs.

Taken together, this chapter establishes both the scientific and operational foundations for the Weather Risk app. By first reviewing rainfall- and temperature-based indices, together with selected water availability indices, the chapter provides a defensible basis for identifying indices that are widely applied, interpretable, and relevant to climate-sensitive decision-making in South Africa, with a particular focus on agriculture. The subsequent review of existing climate databank applications and WCS principles then places these indices within a broader operational context, highlighting how similar information is curated, communicated, and delivered to users through web-based platforms. Collectively, these two strands of review ensure that the Weather Risk app is grounded in established scientific practice while also reflecting recognised principles of effective WCS delivery, thereby supporting its intended role as a practical decision-support tool for agriculture.

2.2 Review of climate and water availability indices

2.2.1 Background to climate and water availability indices: relevance for decision-making

Climate and water availability information can play a critical role in adaptation planning in response to anthropogenic climate change and natural climate variability, yet for such information to be useful in practice, the format in which it is presented is of central importance (Ziervogel et al., 2010; Kiparsky et al., 2012). One widely adopted approach is the use of indices, which statistically summarise daily to monthly data into measures describing average conditions, variability, and extremes (Zhang et al., 2011). These summaries enable more efficient interpretation of complex climate datasets and facilitate the assessment of variability patterns and long-term trends (Zhang et al., 2011; Wiréhn, 2021). When expressed as indices, climate and water availability information can be particularly valuable for addressing questions related to aspects of the climate system that affect both human and natural systems (Xu & Wu, 2017).

In a South African context, climate and water availability information provided to key stakeholders is not always tailored in the form of indices that directly support decision-making. Therefore, an important step towards improving the usability of such information is to review existing indices in terms of their definitions, calculation methods, intended purpose, and documented applications (e.g., Wiréhn, 2021). This process supports the identification of indices that are both scientifically robust and practically relevant, thereby enhancing the potential for climate information to inform decision-making in sectors such as agriculture and water resource management (Vaughan & Dessai, 2014; Bruno Soares et al., 2018).

To provide a clear foundation for this review, it is necessary to define climate and water availability indices as they are used in this report. An index is understood here as a numerical or statistical measure that represents specific characteristics of a dataset. A climatic index refers to a rainfall- and/or temperature-based index that summarises rainfall and/or temperature conditions for a historical, current, or future period. A water availability index refers to an index describing components of the water balance (e.g., evaporation or evapotranspiration and storage), with a focus on surface water and groundwater resources, and may likewise be derived for historical, near-real-time, and forecast/projection contexts. Importantly, the practical utility of these indices depends on their ability to be derived consistently from observational records, near-real-time monitoring data, weather forecasts, or climate projections.

Climate and water availability indices are widely applied in South African research and operational contexts (Kruger & Nxumalo, 2017b; Botai et al., 2021; van der Walt & Fitchett, 2021b; Malherbe et al., 2025), in part because of the availability of software tools that facilitate their calculation from point-based station data and gridded datasets. In the R programming environment, some commonly used packages include Climpact (Herold & McComb, 2023), Bioclim (Serrano-Notivoli, 2023), ClimInd (Reig-Gracia et al., 2021), and heatwaveR (Schlegel & Smit, 2018), while Python-based tools include Icclim (CERFACS, 2025), and Xclim (Bourgault et al., 2023). These tools provide standardised and reproducible methods for calculating a wide range of indices and therefore offer a useful starting point for identifying indices that are relevant for application in South Africa, and of course in general. In the context of this project, indices documented within these packages and demonstrated in South African applications informed the initial pool of indices considered in the review.

In addition to software-based implementations, several data products provide climate and water availability information directly as indices. These include datasets, available through the Copernicus Climate Data Store (CDS; ECMWF, 2026) and the PANGAEA Earth and Environmental Science data publisher (AWI & MARUM, 2026), such as global bioclimatic indicators (Wouters et al., 2021), climate extremes, and heat stress indicators (Sandstad et al., 2022), agroclimatic indicators (Nobakht et al., 2019), CMCC-BioClimInd (Noce et al., 2019), and the FutureStreams dataset (Wanders et al., 2019). Such products further illustrate the growing role of indices as a means of delivering climate information in a form that is readily interpretable and applicable for decision-making, and they therefore represent an additional source of indices considered in this review.

From a decision-making perspective, climate and water availability indices can provide information that supports stakeholders in anticipating, preparing for, and responding to climate variability and change (Zhang et al., 2011; Mahlstein et al., 2015). This is largely because indices are often closely linked to climate impacts experienced by climate-sensitive activities, making them more intuitive and illustrative than raw climate variables alone (Mahlstein et al., 2015). For example, information on the number of dry days during a summer growing season can offer a direct and interpretable explanation for reduced crop yields. In this way, indices allow for more direct quantification of the implications of climate conditions for environmental systems and economic sectors (Bhend et al., 2017).

While indices describing mean conditions remain important, indices that characterise variability and extremes are often more user-friendly and relatable for stakeholders (Mahlstein et al., 2015; Bhend et al., 2017). Consequently, this review considers a range of indices spanning from mean to extreme conditions. Consistent with the focus of this objective, the review is limited to rainfall- and temperature-based climatic indices, while water availability indices focus on surface water and groundwater estimations. Furthermore, only indices that can be applied consistently across the entirety of South Africa are considered to compile a list of indices that are relevant to stakeholders operating in diverse climatic regions.

2.2.2 Literature review methodology

To identify climatic (rainfall- and temperature-based) and water availability indices that have been applied in a South African context, a targeted literature review was undertaken. The review focused on empirical studies that utilised indices derived from observational datasets, reanalysis products, and/or model outputs, and that demonstrated relevance for climate-sensitive sectors such as agriculture and water resource management. The literature review followed a structured but targeted approach, similar to that adopted by van der Walt and Fitchett (2022) and Wiréhn (2021), and was designed to identify many commonly used and operationally relevant indices rather than to provide an exhaustive synthesis of all available studies. As such, the review prioritised indices that have been repeatedly applied in a South African context and that are suitable for consistent calculation using weather station or gridded datasets.

Literature searches were conducted using Google Scholar, ScienceDirect, and Web of Science. An initial set of search terms was based on widely used R and Python packages for the calculation of climate indices, which were used as entry points to identify studies applying such indices over South Africa. These included combinations of package names with South Africa, such as Climpact, Bioclim, ClimInd, ECA&D, heatwaveR, Icclim, Xclim, and Climate_indices. This approach facilitated the identification of rainfall- and temperature-based indices that are computationally accessible, reproducible, and therefore suitable for integration into a web-based application.

Subsequent searches focused specifically on rainfall indices applied in South Africa, using keywords related to rainfall seasonality, average rainfall characteristics, and dry or extreme rainfall conditions (e.g., rainfall seasonality, wet season rainfall, heavy rainfall, dry spells, and other specific index names). A parallel search strategy was employed for temperature indices, with keywords targeting temperature seasonality, mean conditions, hot extremes, and cold extremes (e.g., heatwaves, frost days, extreme temperatures, and other specific index names). Targeted searches were also undertaken for water availability indices relevant to South Africa, with emphasis on indices describing physical water availability, including surface water, groundwater, soil moisture, and evaporation or evapotranspiration. Keywords included combinations of water availability, streamflow, soil moisture, groundwater, and specific index names. Indices based on relative water supply and demand, as well as water quality indicators, were not considered and are beyond the scope of this review. For inclusion in this review, studies were required to be published as peer-reviewed journal articles and to include an empirical application of rainfall, temperature, or water availability indices within South Africa This approach ensured that the reviewed indices are both scientifically established and practically applicable within the South African context.

The outcome of this review is therefore a curated set of rainfall, temperature, and water availability indices that have demonstrated relevance for operational decision-making and that are potentially suitable for inclusion in the Weather Risk application. The indices identified through this review represent those considered during the conceptualisation and design phase of the Weather Risk app. While all indices reviewed were evaluated in terms of their relevance, data requirements, and potential operational usefulness, not all indices were ultimately implemented in the operational platform. Final selection of indices for inclusion in the app was guided by additional considerations, including data availability, computational feasibility, and user relevance, and is described in subsequent chapters.

2.2.3 Rainfall indices

Rainfall indices represent statistical measures used to characterise different aspects of rainfall behaviour over a specified area and time period (Zhang et al., 2011). In the South African context, rainfall indices are particularly valuable given the country's high interannual and intra-seasonal rainfall variability, strong spatial gradients in rainfall climatology, and the sensitivity of agricultural and water-resource systems to rainfall timing, intensity, and persistence (Reason, 2017).

For climate-sensitive activities such as rain-fed agriculture, livestock production, and water-resource management, rainfall indices provide information that extends beyond seasonal or annual rainfall totals (e.g., Ambrosino et al., 2014). By framing rainfall conditions in terms of agriculturally meaningful characteristics, such as season onset, season length, frequency of rain days, and the occurrence of prolonged dry spells, indices offer a more direct link between climate conditions and on-the-ground impacts (Simanjuntak et al., 2023).

In this review, rainfall indices are grouped into four categories:

1) rainfall seasonality indices;
2) average rainfall indices;
3) moderate to extreme rainfall indices; and
4) dry rainfall indices.

These groupings reflect both common practice in the literature and the practical relevance of the indices for operational decision-making. The indices summarised in Table 2.1 are not exhaustive, but they include those commonly applied in South African rainfall studies and provide a basis for evaluating rainfall characteristics relevant to climate-sensitive activities. Collectively, these rainfall index groups were reviewed with consideration of their relevance for climate-sensitive decision-making in South Africa and their suitability for application within an operational, national-scale weather and climate information platform.

Table 2.1: Rainfall indices relevant to South African decision-making. References listed are indicative examples of applications of the listed indices within a South African context.

Index name	Index description and calculation	Units	Time scale	Example reference(s)
		Rainfall seasonality indices		
Seasonality score index	Seasonality score describing the timing and degree of rainfall seasonality, derived as the m-coefficient of the least-squares linear regression between mean monthly rainfall and mean monthly temperature.	Dimensionless	Annual	Roffe et al. (2021a, 2021b, 2022, 2024)
Percentile-based wet season start date	Start date of the rainfall season defined as the date when 10% of annual rainfall has accumulated within a climatologically defined year.	Julian day	Annual	Roffe et al. (2020, 2021b, 2022)
Percentile-based wet season end date	End date of the rainfall season defined as the date when 90% of annual rainfall has accumulated within the climatologically defined year.	Julian day	Annual	Roffe et al. (2020, 2021b, 2022)
Threshold-determined onset (or start) date	Onset (or termed start) date defined using fixed rainfall periods (commonly pentads, 5-day periods, or dekads, 10-day periods) as the first day of the first	Julian day	Annual	Moeletsi & Walker (2012); Ndebele et al. (2022); Roffe et al. (2025)

Index name	Index description and calculation	Units	Time scale	Example reference(s)
	rainfall period in which accumulated rainfall exceeds a specified threshold or the long-term mean rainfall for that period. Definitions of the rainfall period length and threshold vary across studies and are adapted to the prevailing rainfall regime.			
Threshold-determined termination (or cessation or end) date	Termination (or termed cessation or end) date defined using fixed rainfall periods (commonly pentads or dekads) as the last day of the final rainfall period, occurring after onset, in which accumulated rainfall exceeds a specified threshold or long-term mean. Termination may alternatively be defined as the first rainfall period in which accumulated rainfall falls below a threshold or the long-term mean, depending on study objectives and rainfall regime.	Julian day	Annual	Moeletsi & Walker (2012); Ndebele et al. (2022); Roffe et al. (2025)
Wet (dry) season duration	Duration of the wet (dry) season defined as the number of days between onset/start (cessation/termination/end) and cessation/termination/end (onset/start) dates.	Days	Annual	Ndebele et al. (2022); Roffe et al. (2022)
Wet (dry) season total rainfall	Total rainfall accumulated between onset/start (cessation/termination/end) and cessation/termination/end (onset/start) dates.	mm	Annual	Ndebele et al. (2022); Roffe et al. (2022)
Wet (dry) season number of rain days	Total number of rain days between onset/start (cessation/termination/end) and cessation/termination/end (onset/start) dates.; rain day threshold is user-defined.	Days	Annual	Ndebele et al. (2022); Roffe et al. (2022)

Index name	Index description and calculation	Units	Time scale	Example reference(s)
Wet (dry) season daily rainfall rate	Average rainfall per rain day occurring between onset/start (cessation/termination/end) and cessation/termination/end (onset/start) dates.	$mm.day^{-1}$	Annual	Ndebele et al. (2022; Roffe et al. (2022)
		Average rainfall indices		
Total wet-day rainfall	Total rainfall accumulated on days exceeding a user-defined rain-day threshold	mm	Pentad, dekad, monthly, seasonal, annual	Kruger (2006); Lennard & Hegerl (2014); MacKellar et al. (2014); Davis et al. (2016); van Wilgen et al. (2016); Kruger & Nxumalo (2017b); Jury (2018); Mosase & Ahiablame (2018); Tfwala et al. (2018); Burls et al. (2019); Mahlalela et al. (2019, 2020); Ndebele et al. (2020); Wolski et al. (2020); Dosio et al. (2021, 2022); Adeola et al. (2022)
Number of rain (i.e., wet) days	Count of days with rainfall exceeding a user-defined threshold.	Days	Pentad, dekad, monthly, seasonal, annual	Diallo et al. (2014); MacKellar et al. (2014); van Wilgen et al. (2016); Pohl et al. (2017); Tfwala et al. (2018); Burls et al. (2019); Dosio et al. (2021, 2022); Ndlovu et al. (2021)
Average daily rainfall (also termed simple daily intensity index)	Ratio of total rainfall to the number of rain days.	$mm.day^{-1}$	Pentad, dekad, monthly, seasonal, annual	New et al. (2006); Diallo et al. (2014); Davis et al. (2016); Zengeni et al. (2016); Kruger & Nxumalo (2017b); Burls et al. (2019); Dosio et al. (2021, 2022)
		Moderate to extreme rainfall indices		
Consecutive wet days	Maximum number of consecutive wet days based on a user-defined rain-day threshold.	Days	Monthly, seasonal, annual	Kruger (2006); New et al. (2006); Diallo et al. (2014); Davis et al. (2016); Kruger & Nxumalo (2017b); Han et al. (2019); Ndlovu et al. (2021)
Moderate rain days	Number of days when the daily rainfall amount ranges	Days	Pentad, dekad, monthly,	Kruger (2006); Kruger & Nxumalo (2017b); Rapolaki et al.

Index name	Index description and calculation	Units	Time scale	Example reference(s)
	from 10-25 (or 10-30) mm/day (study dependent).		seasonal, annual	(2020); Thoithi et al. (2021)
Significant rain days	Number of days when the daily rainfall amount exceeds the 90th percentile (study dependent).	Days	Pentad, dekad, monthly, seasonal, annual	Dyson (2009); McBride et al. (2022)
Heavy rain days (or termed very wet days)	Number of days when the daily rainfall amount exceeds 10 mm, or 25 mm, or exceeds the 95th percentile (study dependent).	Days	Pentad, dekad, monthly, seasonal, annual	New et al. (2006); Dyson (2009); Lumsden et al. (2009); Davis et al. (2016); Kruger & Nxumalo (2017b); Mahlalela et al. (2020); Rapolaki et al. (2020); McBride et al. (2022)
Very heavy rain days (or termed extremely wet days)	Number of days when the daily rainfall amount exceeds 20 mm, or 30 mm, or exceeds the 99th percentile (study dependent).	Days	Pentad, dekad, monthly, seasonal, annual	Kruger (2006); New et al. (2006); Dyson (2009); Lumsden et al. (2009); Diallo et al. (2014); Davis et al. (2016); Kruger & Nxumalo (2017b); Ndlovu et al. (2021); Conradie et al. (2022); McBride et al. (2022)
Number of extreme rain days	Number of days when the daily rainfall amount exceeds the 95th percentile.	Days	Pentad, dekad, monthly, seasonal, annual	Diallo et al. (2014); Rapolaki et al. (2019); Mpungose et al. (2022)
Maximum one-day rainfall amount	Maximum one-day rainfall total.	mm	Pentad, dekad, monthly, seasonal, annual	Kruger (2006); New et al. (2006); van Wilgen et al. (2016); Kruger & Nxumalo (2017b); Tfwala et al. (2018)
Maximum five-day rainfall amount	Maximum five-day rainfall total.	mm	Pentad, dekad, monthly, seasonal, annual	Kruger (2006); New et al. (2006); Davis et al. (2016); Kruger & Nxumalo (2017b)
Very wet days rainfall contribution	Percentage of rainfall occurring during rain days exceeding the 95th percentile.	%	Pentad, dekad, monthly, seasonal, annual	Kruger (2006); Davis et al. (2016); Kruger & Nxumalo (2017b)
Extremely wet days rainfall contribution	Percentage of rainfall occurring during rain days exceeding the 99th percentile.	%	Pentad, dekad, monthly, seasonal, annual	Kruger (2006); Kruger & Nxumalo (2017b)
		Dry rainfall indices		
Dry spell frequency	Number of 5-day periods (i.e., pentads) with below 5 mm of rain; or number of periods of at least 5 consecutive dry days (user-	number	Monthly, seasonal, annual	Cook et al. (2004); Usman & Reason (2004); Reason et al. (2005); Masupha et al. (2016); Zengeni et

Index name	Index description and calculation	Units	Time scale	Example reference(s)
	defined rain-day threshold); or number of pentads below 15 mm of rain; or a period of consecutive dry days.			al. (2016) Han et al. (2019); Marumbwa et al. (2019); Mengistu et al. (2021); Thoithi et al. (2021); Daniel et al. (2023)
Average dry spell length	Average length of dry spell periods, with at least 5 consecutive dry days (user-defined rain day).	days	Monthly, seasonal, annual	Masupha et al. (2016); Mengistu et al. (2021)
Consecutive dry days (or termed maximum dry spell length)	Maximum number of consecutive dry rain days, where a dry day is recorded as no rainfall or rainfall amount less than the user-defined rain day.	days	Monthly, seasonal, annual	Diallo et al. (2015); Davis et al. (2016); Masupha et al. (2016); Shoko et al. (2016); van Wilgen et al. (2016); Zengeni et al. (2016); Kruger & Nxumalo (2017b); Dosio et al. (2021, 2022); Ndlovu et al. (2021)
Count of dry days	Number of dry days, where a dry day is recorded as no rainfall or rainfall amount less than the user-defined rain day.	days	Pentad, dekad, monthly, seasonal, annual	Lumsden et al. (2009); van Wilgen et al. (2016)

2.2.3.1 Rainfall seasonality indices

Rainfall seasonality indices represent statistical measures used to describe the timing, duration, and distribution of rainfall within a year (Roffe et al., 2021a). These indices focus on when rainfall occurs, how concentrated it is within specific periods, and how wet and dry seasons are structured, rather than on total rainfall amounts alone (Roffe et al., 2021a). In South Africa, where rainfall regimes vary markedly across summer, winter, and year-round rainfall regions, rainfall seasonality indices provide essential information for characterising spatial and temporal differences in rainfall behaviour (Reason, 2017).

From a decision-making perspective, rainfall seasonality indices are particularly valuable because they directly relate to the timing of climate-sensitive activities (Feng et al., 2013). Indices describing wet season onset and termination dates provide information critical for crop planting and harvesting decisions, irrigation scheduling, and rangeland management (Moeletsi & Walker, 2012; Dunning et al., 2016). Measures of wet and dry season duration, together with wet or dry season rainfall totals and rain-day counts, help quantify the length and effectiveness of rainfall seasons, distinguishing between short but intense seasons and longer, less productive ones (Feng et al., 2013; Dunning et al., 2016; Roffe et al., 2021b). The seasonality score index complements these measures by providing a summary indicator of the degree and timing of rainfall seasonality, which can assist in comparing rainfall regimes across regions and identifying shifts in seasonal rainfall characteristics relevant to agricultural planning and water-resource management (Roffe et al., 2021a).

In the South African literature, rainfall seasonality indices have been widely used to investigate climatological patterns (Roffe et al., 2021a), interannual variability characteristics (Moeletsi & Walker, 2012; Dunning et al., 2016), and long-term changes in rainfall timing across different rainfall regimes (Ndebele et al., 2022; Roffe et al., 2021a, 2022). Studies have commonly applied percentile-based approaches to define wet season start and end dates, using accumulated rainfall thresholds (e.g., 10% and 90% of annual rainfall) within a climatologically defined year (Roffe et al., 2020), as well as threshold-based methods that define onset and termination using fixed rainfall periods such as pentads or dekads (Moeletsi & Walker, 2012). These indices were typically evaluated at annual time scales but were informed by sub-monthly rainfall structure. In addition to onset and termination metrics, studies frequently derived secondary seasonality characteristics, including wet and dry season duration, total rainfall, number of rain days, and average daily rainfall rates within each season (Roffe et al., 2022). The rainfall seasonality indices summarised in Table 2.1, therefore, reflect established approaches used to characterise rainfall timing and season structure relevant to climate-sensitive decision-making in South Africa.

2.2.3.2 Average rainfall indices

Average rainfall indices represent statistical measures used to characterise the overall magnitude and intensity of rainfall over a specified period (van Wilgen et al., 2016; Kruger & Nxumalo, 2017b). These indices summarise accumulated rainfall amounts, the frequency of rain days, and the average rainfall rate, thereby providing a general overview of rainfall conditions and their distribution in time (Burls et al., 2019; Dosio et al., 2021, 2022). In the South African context, where rainfall exhibits strong spatial and temporal variability and pronounced interannual fluctuations, such indices form a foundational component of rainfall assessment across multiple temporal scales (Reason, 2017).

From a decision-making perspective, average rainfall indices provide essential baseline information for climate-sensitive activities, particularly agriculture and water-resource management. Total wet-day rainfall indicates the overall moisture input available over a given period and is directly relevant to crop water availability, rangeland productivity, and surface water recharge (MacKellar et al., 2014; Kruger & Nxumalo, 2017b; Mahlalela et al., 2019, 2020). The number of rain days complements this by indicating how rainfall is distributed through time, information that is important for understanding soil moisture replenishment, crop establishment, and grazing conditions (Pohl et al., 2017; Tfwala et al., 2018; van Wilgen et al., 2016). The average daily rainfall, also referred to as the simple daily intensity index, provides insight into rainfall intensity by relating accumulated rainfall to the number of rain days, which can help distinguish between seasons dominated by frequent light rainfall and those characterised by fewer, heavier rainfall events (Davis et al., 2016; Kruger & Nxumalo, 2017b; Burls et al., 2019). Together, these indices can support more informed decisions related to planting schedules, irrigation planning, crop selection, and water allocation.

In the South African literature, average rainfall indices are among the most widely applied rainfall metrics (Table 2.1) and have routinely been used to describe climatological conditions (e.g., Lennard & Hegerl, 2015), assess trends (e.g., Kruger & Nxumalo, 2017b), and evaluate variability patterns in observational datasets, gridded datasets, and climate model simulations (e.g., Wolski et al., 2020; Dosio et al., 2021, 2022). Studies commonly have calculated these indices at monthly, seasonal, and annual time scales, with seasons defined either using standard meteorological seasons or context-specific wet and dry seasons (e.g., Ndebele et al., 2020; Roffe et al., 2022). Applications range from national-scale assessments of rainfall trends and variability to regional and sector-specific analyses focused on agriculture, ecosystems, and water resources (e.g., van Wilgen et al., 2016). The average rainfall indices considered in this review, and summarised in Table 2.1, therefore, represent well-established and widely used measures that provide essential context for understanding rainfall behaviour relevant to decision-making in South Africa.

2.2.3.3 Moderate to extreme rainfall indices

Moderate to extreme rainfall indices represent statistical measures used to characterise the occurrence, frequency, duration, and intensity of higher-than-normal rainfall events (Davis et al., 2016; Kruger & Nxumalo, 2017b; Rapolaki et al., 2019). These indices focus on rainfall extremes and persistent wet conditions, capturing aspects of rainfall behaviour that are not reflected by average rainfall measures (van Wilgen et al., 2016; Kruger & Nxumalo, 2017b; Thoithi et al., 2021). In South Africa, where rainfall often occurs in short, intense events and contributes disproportionately to total seasonal rainfall, moderate to extreme rainfall indices provide important information on rainfall variability patterns and extremes (Thoithi et al., 2021).

From a decision-making perspective, moderate to extreme rainfall indices are particularly relevant for both agricultural management and water-resource planning. Indices such as consecutive wet days and counts of moderate, heavy, and very heavy rainfall days provide insight into the persistence and intensity of rainfall events, which can influence soil saturation, runoff generation, crop damage risk, and the timing of agricultural operations (Davis et al., 2016; Thoithi et al., 2021; Conradie et al., 2022). Measures of maximum one-day and five-day rainfall totals are especially relevant for assessing flood potential, erosion risk, and infrastructure vulnerability (van Wilgen et al., 2016; Kruger & Nxumalo, 2017b), while indices describing the contribution of very wet and extremely wet days to total rainfall help quantify the extent to which seasonal rainfall is dominated by extreme events (Rapolaki et al., 2019; Mpungose et al., 2022). In agricultural contexts, this information can inform crop selection, planting and harvesting schedules, and crop protection strategies, while for water managers it can support planning related to dam storage, flood mitigation, and catchment management.

In the South African literature, moderate to extreme rainfall indices have widely been applied in studies examining rainfall climatology (Thoithi et al., 2021), variability patterns (Rapolaki et al., 2019; Mpungose et al., 2022), and long-term trend analysis using station observations, gridded datasets, and climate model projections (Kruger & Nxumalo, 2017b; McBride et al., 2022). These indices have commonly been analysed at monthly, seasonal, and annual time scales, with many studies focusing on the extended summer rainfall season, which coincides with the primary crop growing period over much of the country (Rapolaki et al., 2019) Applications have included assessments of changes in rainfall intensity and persistence (McBride et al., 2022), and investigations of the contribution of extreme rainfall events to total precipitation (Conradie et al., 2022). A broad range of indices has been employed, including counts of consecutive wet days, threshold- and percentile-based rainfall day counts, maximum multi-day rainfall amounts, and measures of rainfall contribution from very wet and extremely wet days (Table 2.1). The moderate to extreme rainfall indices summarised in Table 2.1, therefore, reflect well-established approaches used to characterise rainfall extremes relevant to climate-sensitive decision-making in South Africa.

2.2.3.4 Dry rainfall indices

Dry rainfall indices represent statistical measures used to characterise the frequency, duration, and persistence of rainfall deficits over a given period (Masupha et al., 2016; van Wilgen et al., 2016). Rather than focusing on total rainfall amounts, these indices describe periods of limited or absent rainfall, thereby capturing aspects of intra-seasonal rainfall variability that are not reflected in average conditions (Mengistu et al., 2021; Daniel et al., 2023). In South Africa, where rainfall is often episodic and unevenly distributed within the rainy season, dry rainfall indices provide critical insight into short-term moisture stress and rainfall interruptions (Thoithi et al., 2021).

From a decision-making perspective, dry rainfall indices are particularly valuable for climate-sensitive activities such as rain-fed agriculture, livestock production, and water-resource management (Masupha et al., 2016; Ndlovu et al., 2021; Daniel et al., 2023). Measures such as dry spell frequency and consecutive dry days provide information on the likelihood and persistence of rainfall interruptions, which can directly affect crop establishment, pasture growth, and soil moisture availability (Masupha et al., 2016; Kruger and Nxumalo, 2016b). Average dry spell length and the count of dry days offer additional insight into the cumulative severity of dry conditions within a season, helping to distinguish between occasional short dry spells and prolonged dry periods (van Wilgen et al., 2016; Mengistu et al., 2021). In an agricultural context, this information can inform planting decisions, supplementary irrigation planning, and grazing management, while for water managers it can support assessments of short-term water stress and guide the timing of water-saving interventions (Masupha et al., 2016). Importantly, while these indices can act as meteorological indicators of short-term dryness, they are distinct from formal drought indices and provide complementary information focused on rainfall persistence rather than longer-term water deficits.

In the South African literature, dry rainfall indices have widely been applied to assess intra-seasonal rainfall variability (Cook et al., 2004; Usman & Reason, 2004; Reason et al., 2004), dry spell characteristics (Masupha et al., 2016), and their implications for agriculture, ecosystems, and climate extremes (van Wilgen et al., 2016). Studies have commonly analysed indices such as dry spell frequency (Mengistu et al., 2016), average dry spell length (Masupha et al., 2016), consecutive dry days (Dosio et al., 2021, 2022), and the number of dry days (Lumsden et al., 2009), all using station observations, gridded rainfall datasets, and climate model output. These indices have typically been evaluated at monthly, seasonal, and annual time scales, with a strong emphasis on the extended summer rainfall season, corresponding to the main crop growing period across much of the country (Table 2.1). Applications have included climatological assessments (Thoithi et al., 2021), trend analyses (van Wilgen et al., 2016), and variability studies (Mengistu et al., 2021), often in conjunction with temperature-based indices or broader climate analyses (Kruger & Nxumalo, 2017b). The dry rainfall indices summarised in Table 2.1, therefore, represent well-established measures that are routinely used to characterise rainfall interruptions relevant to climate-sensitive decision-making in South Africa.

2.2.4 Temperature indices

Temperature indices represent statistical measures used to characterise different aspects of temperature behaviour over a specified area and temporal period (Zhang et al., 2011). In the South African context, temperature indices are particularly important given the country's wide range of climatic conditions, strong spatial gradients in temperature, and the sensitivity of many climate-dependent systems to both temperature variability and extremes (Reason, 2017).

For climate-sensitive activities such as crop and livestock production, water-resource management, and infrastructure planning, temperature indices provide information that extends beyond mean temperature conditions alone (e.g., Adisa et al., 2018). By framing temperature conditions in terms of agriculturally and operationally meaningful characteristics, such as the timing and length of warm and cold seasons, the frequency and persistence of heat and cold events, and the occurrence of temperature extremes, temperature indices offer a more direct link between climatic conditions and potential impacts experienced on the ground (Simanjuntak et al., 2023).

In this review, temperature indices are grouped into four categories:

1) temperature seasonality indices;
2) average temperature indices;
3) hot temperature indices; and
4) cold temperature indices.

These groupings reflect both common practice in the literature and the practical relevance of the indices for operational decision-making. The temperature indices summarised in Table 2.2 are not exhaustive, but they include those most applied in South African studies and provide a basis for evaluating temperature characteristics relevant to climate-sensitive activities. Collectively, these temperature index groups were reviewed with consideration of their relevance for climate-sensitive decision-making in South Africa and their suitability for application within an operational, national-scale weather and climate information platform.

Table 2.2: Temperature indices relevant to South African decision-making. References listed are indicative examples of applications of the listed indices within a South African context.

Index name	Index description and calculation	Units	Time scale	Example reference(s)
Temperature seasonality indices				
Growing season onset (or start) date	The first day of the growing season, defined as the first day of the first period of at least six consecutive days with daily mean temperature above a specified base temperature (commonly 5 °C) within the climatological year (July-June in the Southern Hemisphere).	Julian day	Annual	New et al. (2006); Moeletsi (2017)
Growing season termination (or	The last day of the growing season,	Julian day	Annual	New et al. (2006); Moeletsi (2017)

cessation or end) date	defined as the first day (after 1 January in the Southern Hemisphere) of the first period of at least six consecutive days with daily mean temperature below the specified base temperature (commonly 5 °C).			
Growing season length	Total number of days between the growing season start and end dates, representing the duration of thermally suitable conditions for plant growth based on daily mean temperature thresholds.	Days	Annual	New et al. (2006); Moeletsi (2017)
		Average temperature indices		
Average temperature	Daily average temperature.	°C	Pentad, dekad, monthly, seasonal, annual	Kruger & Shongwe (2004); van Wilgen et al. (2016); Dosio (2017); Kruger & Nxumalo (2017a); Maúre et al. (2018); Jury (2018); Adeola et al. (2022); Dosio et al. (2022);
Average maximum temperature	Average daily maximum temperature.	°C	Pentad, dekad, monthly, seasonal, annual	MacKellar et al. (2014); Engelbrecht et al. (2015); van Wilgen et al. (2016); Dosio (2017); Kruger & Nxumalo (2017a); Mosase & Ahiablame (2018); Kruger et al. (2019); Ndlovu et al. (2021); Dosio et al. (2022); Mbokodo et al., (2020, 2023)
Average minimum temperature	Average daily minimum temperature.	°C	Pentad, dekad, monthly, seasonal, annual	MacKellar et al. (2014); Davis et al. (2016); van Wilgen et al. (2016); Dosio (2017); Kruger & Nxumalo (2017a);

				Mosase & Ahiablame (2018); Kruger et al. (2019); Dosio et al. (2022); Mbokodo et al. (2020); Ndlovu et al. (2021)
Average diurnal temperature range	Average difference between the daily maximum and minimum temperature.	°C	Pentad, dekad, monthly, seasonal, annual	Kruger & Shongwe (2004); Davis et al. (2016); van Wilgen et al. (2016); Kruger & Nxumalo (2017a); Kruger et al. (2019); Mbokodo et al. (2020)
Hot temperature indices				
Maximum daily maximum temperature	Maximum value of daily maximum temperature.	°C	Pentad, dekad, monthly, seasonal, annual	New et al. (2006); Davis et al. (2016); Kruger & Nxumalo (2017a); Kruger et al. (2019); van der Walt & Fitchett (2021)
Maximum daily minimum temperature	Maximum value of daily minimum temperature.	°C	Pentad, dekad, monthly, seasonal, annual	New et al. (2006); Davis et al. (2016); Kruger & Nxumalo (2017a); Kruger et al. (2019); van der Walt & Fitchett (2021)
Hot days	Number of days when the daily maximum temperature exceeds 25°C.	Days	Pentad, dekad, monthly, seasonal, annual	New et al. (2006); Davis et al. (2016); van der Walt & Fitchett (2021)
Warm nights	Number of days when the daily minimum temperature exceeds 20°C.	Days	Pentad, dekad, monthly, seasonal, annual	New et al. (2006); Kruger & Shongwe (2004); Davis et al. (2016)
Very hot days	Number of days when the daily maximum temperature exceeds 35°C.	Days	Pentad, dekad, monthly, seasonal, annual	Kruger & Shongwe (2004); van der Walt & Fitchett (2021)
Warm days	Percentage of days when daily maximum temperature is above the 90th percentile (or 95th percentile).	%	Pentad, dekad, monthly, seasonal, annual	New et al. (2006); Diallo et al. (2014); Davis et al. (2016); Kruger & Nxumalo (2017a); Kruger et al. (2019); van der Walt & Fitchett (2021); Mbokodo et al. (2020, 2023)
Warm nights	Percentage of days when daily minimum temperature is above the 90th	%	Pentad, dekad, monthly, seasonal, annual	New et al. (2006); Diallo et al. (2014); Kruger & Nxumalo (2017a); Kruger et al. (2019); van der Walt

	percentile (or 95th percentile).			& Fitchett (2021); Mbokodo et al. (2020, 2023)
Warm spell duration indicator	Number of days contributing to events where at least N (e.g., three or six) consecutive days have maximum temperatures above the 90th (or 95th) percentile.	Days	Annual	New et al. (2006); Davis et al. (2016); Kruger & Nxumalo (2017a); Kruger et al. (2019); van der Walt & Fitchett (2021)
User-defined consecutive number of hot days and nights	Annual count of a user-defined number of consecutive days where both maximum and minimum temperature are above the 95th percentile.	Days	Annual	van der Walt & Fitchett (2021)
Heatwave amplitude	Peak daily temperature recorded during the most intense heatwave event within the summer season. Heatwaves are identified using a specified heatwave definition, commonly based on percentile thresholds or excess heat metrics.	°C or $°C^2$	Annual	Meque et al. (2022)
Heatwave duration	Length (in days) of the longest heatwave occurring within the summer season. Heatwaves are identified using a specified heatwave definition, commonly based on percentile thresholds or excess heat metrics.	Days	Annual	Mbokodo et al. (2020); van der Walt & Fitchett (2021); Meque et al. (2022)

Heatwave frequency	Total number of days contributing to heatwave conditions during the summer season within the summer season. Heatwaves are identified using a specified heatwave definition, commonly based on percentile thresholds or excess heat metrics.	Days or events	Annual	Engelbrecht et al. (2015); Mbokodo et al. (2020, 2023); Meque et al. (2022); Roffe & van der Walt (2023); van der Walt et al. (2023)
Heatwave number	The number of individual heatwaves that occur in the summer season. Heatwaves are identified using a specified heatwave definition, commonly based on percentile thresholds or excess heat metrics.	Events	Annual	van der Walt & Fitchett (2021); Meque et al. (2022); Roffe & van der Walt (2023); van der Walt et al. (2023)
Heatwave magnitude (intensity)	Mean, average, maximum or minimum daily temperature recorded during heatwave events within the summer season. Heatwaves are identified using a specified heatwave definition, commonly based on percentile thresholds or excess heat metrics.	°C or °C^2	Annual	Mbokodo et al. (2020); Roffe & van der Walt (2023); van der Walt et al. (2023)
		Cold temperature indices		
Coldest day	Minimum value of daily maximum.	°C	Pentad, dekad, monthly, seasonal, annual	New et al. (2006); Kruger & Sekele (2013); Davis et al. (2016); Kruger & Nxumalo (2017a);

				Kruger et al. (2019); van der Walt & Fitchett (2020b)
Coldest night	Minimum value of daily minimum temperature.	°C	Pentad, dekad, monthly, seasonal, annual	New et al. (2006); Kruger & Sekele (2013); Kruger & Nxumalo (2017a); Davis et al. (2016); Kruger et al. (2019); van der Walt & Fitchett (2020b)
Frost days	Number of days when the daily minimum temperature is below 0°C (or 2°C or -2°C).	Days	Pentad, dekad, monthly, seasonal, annual	Kruger & Shongwe (2004); New et al. (2006); Moeletsi et al. (2016); Moeletsi & Tongwane (2017a); van der Walt & Fitchett (2020b)
Ice days	Number of days when the daily maximum temperature is below 0°C.	Days	Pentad, dekad, monthly, seasonal, annual	New et al. (2006); van der Walt & Fitchett (2020b)
Hard freeze days	Number of days when the daily minimum temperature is below -2°C.	Days	Pentad, dekad, monthly, seasonal, annual	van der Walt & Fitchett (2020b)
Cool days	Percentage of days when daily minimum temperature is below the 10th percentile (or 5th percentile).	%	Pentad, dekad, monthly, seasonal, annual	New et al. (2006); Kruger & Sekele (2013); Diallo et al. (2014); Davis et al. (2016); Kruger & Nxumalo (2017a); Kruger et al. (2019); van der Walt & Fitchett (2020b); Mbokodo et al. (2020, 2023)
Cool nights	Percentage of days when daily maximum temperature is below the 10th percentile (or 5th percentile).	%	Pentad, dekad, monthly, seasonal, annual	New et al. (2006); Kruger & Sekele (2013); Diallo et al. (2014); Davis et al. (2016); Kruger & Nxumalo (2017a); Kruger et al. (2019); van der Walt & Fitchett (2020b); Mbokodo et al. (2020, 2023)
Cold spell duration indicator	Number of days contributing to cold spell events, defined as periods of at least N (e.g., three or	Days	Annual	New et al. (2006); Kruger & Sekele (2013); Davis et al. (2016); Kruger & Nxumalo (2017a); Kruger et al. (2019);

	six) consecutive days during which daily minimum temperatures fall below the 10th (or 5th) percentile.			van der Walt & Fitchett (2020b)
User-defined consecutive number of cold days and nights	Annual count of a user-defined number of consecutive days where both maximum and minimum temperature are below the 5th percentile.	Days	Annual	van der Walt & Fitchett (2020b)
Coldwave duration	Length of the longest coldwave occurring within the winter season. Coldwaves are identified using a specified coldwave definition, commonly based on percentile thresholds or excess cold metrics.	Days	Annual	van der Walt & Fitchett (2020b); Meque et al. (2024)
Coldwave frequency	Total number of days contributing to coldwave conditions during the winter season. Coldwaves are identified using a specified coldwave definition, commonly based on percentile thresholds or excess cold metrics.	Days	Annual	Roffe & van der Walt (2023); Meque et al. (2024)
Coldwave number	Number of distinct coldwave events occurring during the winter season. Coldwaves are identified using a specified coldwave definition, commonly based	Events	Annual	van der Walt & Fitchett (2020b); Roffe & van der Walt (2023); Meque et al. (2024)

	on percentile thresholds or excess cold metrics.			
Coldwave magnitude	Mean average, maximum or minimum cumulative daily temperature recorded during coldwave events within the winter season. Coldwaves are identified using a specified coldwave definition, commonly based on percentile thresholds or excess cold metrics.	$°C^2$	Annual	Roffe & van der Walt (2023); Meque et al. (2024)

2.2.4.1 Temperature seasonality indices

Temperature seasonality indices represent statistical measures used to describe the timing and duration of thermally suitable conditions within a year, rather than fixed calendar-based seasons (Hekmatzadeh et al., 2020). Unlike conventional meteorological seasons, which divide the year into fixed three-month periods, temperature seasonality indices are designed to capture variations in temperature conditions that are directly relevant to biological and socio-economic processes (Hekmatzadeh et al., 2020). In the South African context, where temperature regimes vary strongly across regions and elevation, and where fixed seasonal definitions are not always aligned with agricultural or ecological processes, temperature seasonality indices provide a more flexible and impact-relevant representation of seasonal temperature behaviour (van der Walt & Fitchett, 2020a).

From a decision-making perspective, temperature seasonality indices based on growing season characteristics are particularly valuable for agriculture and land management (New et al., 2006; Moeletsi, 2017). Indices describing growing season onset and termination dates provide information on the timing of thermally suitable conditions for plant growth, which is critical for crop planting, cultivar selection, and harvest planning (New et al., 2006; Moeletsi, 2017). Growing season length offers a summary measure of the duration of favourable thermal conditions and can be used to assess interannual variability, long-term change, and spatial differences in crop suitability (New et al., 2006; Moeletsi, 2017). Because these indices are defined using temperature thresholds rather than fixed calendar periods, they are well suited to identifying shifts in seasonal timing associated with climate variability and change, and to supporting adaptive decision-making under changing thermal regimes (New et al., 2006; Moeletsi, 2017).

In the South African literature, temperature seasonality has most commonly been represented using fixed meteorological seasons (van der Walt & Fitchett, 2020a); however, threshold-based growing season indices have also been applied to examine thermal suitability for agriculture and to assess changes in growing conditions over time (New et al., 2006; Moeletsi, 2017). These indices have typically been derived from daily temperature data and evaluated at annual time scales, with growing seasons defined within a Southern Hemisphere climatological year (New et al., 2006; Moeletsi, 2017). Applications have included climatological assessments, trend analyses, and evaluations of changes in the timing and duration of thermally suitable periods (New et al., 2006; Moeletsi, 2017). Although growing season-based temperature seasonality indices have been less widely applied than other temperature indices in South Africa, they represent robust and interpretable measures for characterising temperature seasonality relevant to climate-sensitive decision-making. The growing season indices summarised in Table 2.2, therefore, provide a focused and operationally meaningful approach to representing temperature seasonality in this review.

2.2.4.2 Average temperature indices

Average temperature indices represent statistical measures used to characterise typical temperature conditions over a given period, capturing central tendencies and variability in near-surface air temperature (Kruger & Nxumalo, 2017a). These indices describe average thermal conditions through measures of mean temperature, average daily maximum and minimum temperatures, and the diurnal temperature range (Table 2.2). In South Africa, where temperature varies strongly across seasons, elevation, and climatic regions, average temperature indices provide a fundamental basis for understanding thermal regimes and their changes over time (Reason, 2017).

From a decision-making perspective, average temperature indices provide essential contextual information for a range of climate-sensitive activities. Average and extreme daily temperatures influence crop development rates, growing season suitability, and harvest timing, while minimum temperatures are particularly relevant for frost risk and crop damage assessments (van Wilgen et al., 2016; Moeletsi, 2017). Average maximum temperatures can inform understanding of evaporative demand, livestock heat stress exposure, and irrigation requirements, while the diurnal temperature range provides insight into temperature variability that can affect plant physiology, pest development, and water demand (Davis et al., 2016; van Wilgen et al., 2016). In water-resource and agricultural planning contexts, these indices support decisions related to crop selection, planting schedules, irrigation planning, and assessments of long-term climate suitability (Kruger & Nxumalo, 2017a).

In the South African literature, average temperature indices are among the most widely applied thermal metrics (Table 2.1) and have routinely been used to describe climatological conditions (e.g., Dosio, 2017; Mbokodo et al., 2020), assess variability characteristics (e.g., Mbokodo et al., 2023), and investigate long-term temperature trends associated with climate change (e.g., Kruger & Nxumalo, 2017a; Kruger et al., 2019). Studies have commonly derived these indices from station observations, gridded datasets, and climate model simulations, analysing them at monthly, seasonal, and annual time scales (MacKellar et al., 2014; Davis et al., 2016; Dosio, 2017; Mosae & Ahiablame, 2018). Seasonal analyses have typically been based on standard meteorological seasons, though user-defined or application-specific definitions are also employed. Average daily temperature has generally been calculated either as the mean of hourly temperatures or as the average of daily minimum and maximum temperatures, while diurnal temperature range is derived as the difference between daily maximum and minimum temperatures. The average temperature indices summarised in Table 2.2, therefore, represent well-established measures that provide essential context for understanding temperature conditions relevant to climate-sensitive decision-making in South Africa.

2.2.4.3 Hot temperature indices

Hot temperature indices represent statistical measures used to characterise the occurrence, frequency, intensity, and persistence of high-temperature conditions across a range of time scales (Kruger & Nxumalo, 2017a; Kruger et al., 2019; van der Walt & Fitchett, 2021). These indices typically focus on the upper tail of the temperature distribution and are commonly derived from daily maximum and, in some cases, daily minimum temperatures (New et al., 2006; van der Walt & Fitchett, 2021). In South Africa, where temperatures exhibit strong spatial gradients and pronounced seasonal variability, hot temperature indices provide critical information for understanding thermal extremes and their potential impacts (Reason et al., 2017).

From a decision-making perspective, hot temperature indices are particularly relevant for a range of activities, including agriculture, livestock management, water-resource planning, and human health. Indices such as maximum daily maximum and minimum temperatures provide information on extreme thermal thresholds that can affect crop physiology, livestock heat stress, and infrastructure performance (New et al., 2006; Davies et al., 2016; van der Walt & Fitchett, 2021). Counts of hot, very hot, and warm days and nights help quantify the frequency of temperature exceedances relevant to crop damage, heat stress, and elevated evaporative demand (Kruger & Shongwe, 2004; Davies et al., 2016; Kruger et al., 2019; van der Walt & Fitchett, 2021). Warm spell and consecutive hot day-night indices capture the persistence of extreme heat conditions, which is especially important for assessing cumulative heat stress impacts (van der Walt & Fitchett, 2021). Heatwave-specific indices, including heatwave amplitude, duration, frequency, number, and magnitude, provide further insight into the severity and structure of extreme heat events (Mbokodo et al., 2020; van der Walt & Fitchett, 2021; Meque et al., 2022). Although heatwaves can be defined for different seasons depending on application, they are most assessed during the summer or extended summer period, when heat-related impacts on agriculture, water demand, and health are typically greatest (Mbokodo et al., 2020).

In the South African literature, hot temperature indices have widely been applied to assess climatological patterns (e.g., van der Walt & Fitchett, 2021; Roffe & van der Walt, 2023), variability characteristics (e.g., Meque et al., 2022), and long-term trends in extreme heat using station observations, gridded datasets, and climate model simulations (e.g., Kruger & Nxumalo, 2017a; Kruger et al., 2019). Studies have commonly focused on summer or extended summer seasons, although some analyses consider year-round conditions or alternative seasonal definitions depending on sectoral relevance (Mbokodo et al., 2020). Applications have included evaluations of changes in the frequency and intensity of hot days and nights (e.g., Kruger et al., 2019) and assessments of warm spell and heatwave characteristics (e.g., Meque et al., 2022). A wide range of threshold-based and percentile-based indices have been employed, reflecting differences in climatic regions and study objectives. The hot temperature indices summarised in Table 2.2, therefore, represent established and widely used measures for characterising extreme heat conditions relevant to climate-sensitive decision-making in South Africa.

2.2.4.4 Cold temperature indices

Cold temperature indices represent statistical measures used to characterise the occurrence, frequency, intensity, and persistence of low-temperature conditions across a range of time scales (van der Walt & Fitchett, 2020b). These indices focus on the lower tail of the temperature distribution and are most derived from daily minimum temperatures, although daily maximum temperatures are also used for certain metrics (van der Walt & Fitchett, 2020b; Roffe & van der Walt, 2023). In South Africa, cold temperature indices remain important despite overall warming trends, as cold events continue to occur and can have significant impacts on climate-sensitive systems (Roffe & van der Walt, 2023).

From a decision-making perspective, cold temperature indices are particularly relevant for agriculture, livestock management, and human health. Indices describing the coldest day and coldest night provide information on extreme low-temperature thresholds that can lead to crop damage and livestock stress (Kruger & Sekele, 2013; van der Walt & Fitchett, 2020b). Counts of frost, ice, and hard freeze days are especially important for identifying frost risk, guiding planting dates, cultivar selection, and the need for protective measures in sensitive crops (Moeletsi et al., 2016; Moeletsi & Tongwane, 2017). Percentile-based indices describing cool days and nights provide additional insight into anomalously cold conditions relative to local climatology (Kruger & Nxumalo, 2017a; van der Walt & Fitchett, 2020b), while cold spell indicators capture the persistence of cold conditions that can exacerbate impacts through cumulative exposure (Kruger et al., 2019). Coldwave indices, including duration, frequency, number, and magnitude, further describe structured cold events (Roffe & van der Walt, 2023; Meque et al., 2024). Although coldwaves can be defined for different seasons depending on application, they are most assessed during the winter or extended winter period, when cold-related impacts on agriculture and human health are typically greatest (Meque et al., 2024).

In the South African literature, cold temperature indices have widely been applied to examine climatological patterns (Roffe & van der Walt, 2023), variability patterns (Meque et al., 2024), and long-term changes in low-temperature extremes using station observations, gridded datasets, reanalysis products, and climate model projections (Kruger & Sekele, 2013; Kruger & Nxumalo, 2017a; Mbokodo et al., 2020). Analyses have commonly been conducted at monthly, seasonal, and annual time scales, with a strong emphasis on winter or extended winter seasons, although some studies also consider growing-season conditions (Moeletsi & Tongwane, 2017; Meque et al., 2024). Applications have included assessments of frost risk (Moeletsi & Tongwane, 2017), evaluations of changes in cold extremes (van der Walt & Fitchett, 2020b), and analyses of cold spell and coldwave characteristics (Meque et al., 2024). A broad range of threshold-based and percentile-based indices have been applied, reflecting differences in regional climate and sectoral relevance. The cold temperature indices summarised in Table 2.2, therefore, represent established and widely used measures for characterising cold conditions relevant to climate-sensitive decision-making in South Africa.

2.2.5 Water availability indices

In the context of this report, water availability indices represent statistical measures used to assess the physical availability of surface water and groundwater resources within a region, including water stored in rivers, reservoirs, aquifers, and soil (Xu & Wu, 2017). These indices typically represent components of the water balance and provide information on the state and variability of available water resources (Xu & Wu, 2017). As such, water availability indices support decision-making related to water management, policy development, and resource allocation, and can also inform operational decisions in climate-sensitive sectors such as agriculture (du Plessis, 2017; Liu et al., 2022).

In South Africa, water availability is widely recognised as a major constraint to socioeconomic development (Matchaya et al., 2019). The country is often described as water-scarce and frequently faces challenges associated with water scarcity, defined as a lack of sufficient available freshwater resources to sustainably meet societal and economic demands (Matchaya et al., 2019). In this context, physical water scarcity occurs when water demand exceeds available supply within a given region, while economic water scarcity arises when inadequate infrastructure or management limits access to available water resources (Xu & Wu, 2017). Quantifying water availability is therefore a critical component of effective water-resource management and planning (du Plessis, 2017).

To support the interpretation of hydroclimatic conditions, water availability indices are reviewed here alongside climatic indices. Total available water resources are commonly divided into blue water and green water components (Matchaya et al., 2019). Blue water refers to surface and subsurface water resources, including rivers, lakes, dams, and aquifers, that are accessible for multiple uses, while green water represents soil moisture that is available for evapotranspiration and plant growth (Schuol et al., 2008). Following this conceptual framework, water availability indices in this review are grouped into two broad categories:

1) blue water indices; and
2) green water indices.

In grouping water availability indices, it is acknowledged that water availability can also be defined in terms of the balance between water supply and demand (Xu & Wu, 2017). While several approaches have been developed to quantify water availability from a supply-demand perspective, such as water footprint, life cycle assessment, and hydrological methods (Le Roux et al., 2018), the complexity of defining water availability across different spatial and temporal scales has resulted in no single standardised approach. Indices that explicitly quantify relative water supply and demand, as well as indices related to water quality, are therefore considered beyond the scope of this report. Instead, this review focuses on indices that quantify the physical availability of water resources and that can be derived from readily available datasets. Details of the water availability indices considered are provided in Table 2.3. Collectively, these water availability index groups were reviewed with consideration of their relevance for water-resource decision-making in South Africa and their suitability for application within an operational hydroclimatic information platform.

Table 2.3: Water availability indices relevant to South African decision-making. References listed are indicative examples of applications of the listed indices within a South African context.

Index name	Index description and calculation	Units	Time scale	Example reference(s)
Blue water indices				
Average streamflow	Average daily streamflow.	$m^3.s$	Monthly to Annual	Aich et al. (2014); Sunday et al. (2014); Odiyo et al. (2015);

				Lakhraj-Govender & Grab (2019); Botai et al. (2020, 2021); Watson et al. (2021); Banda et al. (2022); Ekolu et al. (2022)
Average daily maximum streamflow	Average daily maximum streamflow.	$m^3.s$	Monthly to Annual	Watson et al. (2021)
Average daily minimum streamflow	Average daily minimum streamflow.	$m^3.s$	Monthly to Annual	Watson et al. (2021)
Standardised streamflow index	Streamflow dryness or wetness level calculated based on the deviation of streamflow from normal (average) conditions.	Dimensionless	Monthly to Annual	Botai et al. (2020, 2021); Ekolu et al. (2022); Mukhawana et al. (2023)
Streamflow percentiles	Levels of streamflow based on percentiles, including the 10th and 90th percentile for example.	$m^3.s$	Monthly to Annual	Aich et al. (2014); Botai et al. (2020); Watson et al. (2021); Mukhawana et al. (2023)
Percentage of available surface water (dam, reservoir, lake and river)	A remote sensing index (e.g., Normalised Difference Water Index, Modified Normalised Difference Water Index and Land Surface Water Index) of surface water availability based on the actual surface water storage capacity, volumetric area, and the volumetric water area measured for the month under assessment.	%	Monthly to Annual	Janovic et al. (2014); Thompson et al. (2018); Seaton et al. (2020); Bhaga et al. (2020, 2021); Seaton & Dube (2021)
Average dam (or reservoir) level	Average daily dam (or reservoir) level or percentage of water available compared to full storage capacity.	Mm^3 or %	Monthly to Annual	Botai et al. (2018); Burls et al. (2019); Mahlalela et al. (2020)
Surface water supply index	Surface water availability level, calculated using rainfall amount, streamflow amount and surface reservoir level.	Dimensionless	Monthly to Annual	Mukhawana et al. (2023)
Average groundwater level	Daily average groundwater level.	m	Monthly to Annual	Makungo & Odiyo (2017); Abiye et al. (2018); Ndlovu & Demlie (2018);

				Ramjeawon et al. (2022)
Standardised groundwater index	Based on groundwater levels, groundwater dryness or wetness level is calculated based on the deviation of groundwater levels from normal (average) conditions.	Dimensionless	Monthly to Annual	Sorensen et al. (2021)
		Green water indices		
Average soil moisture	Daily average soil moisture.	mm or $m^3.m^3$ or %	Monthly to Annual	Vey et al. (2016); Myeni et al. (2022); Yuan et al. (2022)
Average maximum soil moisture	Average daily maximum soil moisture.	mm or $m^3.m^3$ or %	Monthly to Annual	Myeni et al. (2022)
Average minimum soil moisture	Average daily minimum soil moisture.	mm or $m^3.m^3$ or %	Monthly to Annual	Myeni et al. (2022)
Soil moisture deficit	Level of soil moisture deficit based on the actual soil moisture in relation to the maximum soil moisture.	mm or $m^3.m^3$ or %	Monthly to Annual	Mukhawana et al. (2023)
Soil moisture drought index	Soil moisture dryness or wetness level calculated based on soil water (moisture) deficit derived from values of minimum, maximum and median soil moisture.	Dimensionless	Monthly to Annual	Watson et al. (2022)
Average evaporation/evapotranspiration	Daily average evaporation/evapotranspiration.	mm or $mm.day^{-1}$	Monthly to Annual	Jovanovic et al. (2011, 2015); Clulow et al. (2012); Trambauer et al. (2014); Shoko et al. (2015, 2016); Tongwane et al. (2017); Dzikiti et al. (2019); Khosa et al. (2019); Onyutha (2021); Rapolaki et al. (2021)

2.2.5.1 Blue water indices

Blue water indices represent statistical measures used to quantify the physical availability of surface water and groundwater resources, including river flow, dam and reservoir storage, and groundwater levels (Schuol et al., 2008; Xu & Wu, 2017; Khand et al., 2021). These indices capture variations in water stored within rivers, lakes, reservoirs, and aquifers, and provide information on both average conditions and deviations from normal states (Schuol et al., 2008). In South

Africa, where surface and groundwater resources are highly variable in space and time, blue water indices are essential for characterising water availability at catchment to national scales.

From a decision-making perspective, blue water indices can provide critical information for water-resource planning, allocation, and management. Streamflow indices, such as average, minimum, and maximum flow, support assessments of water availability for domestic, agricultural, and industrial use, while also informing flood and low-flow risk management (Lakhraj-Govender & Grab, 2019; Botai et al., 2020, 2021; Watson et al., 2021). Standardised streamflow indices and streamflow percentiles provide interpretable measures of relative wetness or dryness, enabling comparisons across regions and time periods (Botai et al., 2020, 2021; Watson et al., 2021; Mukhawana et al., 2023). Indices describing dam and reservoir levels, as well as surface water extent derived from remote sensing, are particularly valuable for operational water management, as they directly reflect storage conditions relevant to supply planning and restriction decisions(Botai et al., 2018; Thompson et al., 2018; Seaton et al., 2020; Seaton & Dube, 2021). Groundwater indices, including average groundwater levels and standardised groundwater indices, complement surface water measures by providing insight into subsurface water availability, which is especially important in regions reliant on groundwater for irrigation and rural water supply(Abiye et al., 2018; Sorensen et al., 2021).

In the South African literature, blue water indices have widely applied in studies examining hydrological variability, trends, and responses to climate variability and change(Botai et al., 2020, 2021; Watson et al., 2021; Mukhawana et al., 2023). Streamflow indices have commonly been derived from monitoring data and hydrological model simulations (Sunday et al., 2014; Lakhraj-Govender & Grab, 2019; Ekolu et al., 2022), while dam and reservoir levels have routinely been analysed using in situ measurements and, increasingly, satellite-based observations (Botai et al., 2018; Thompson et al., 2018). Remote sensing-based surface water indices have been used to characterise spatial patterns and temporal changes in water extent, particularly where monitoring networks are sparse(Thompson et al., 2018; Maake et al., 2023). Groundwater indices have typically been derived from borehole observations, with emerging applications of satellite-based estimates of terrestrial water storage to supplement in situ data(Makungo & Odiyo, 2017; Abiye et al., 2018). These indices have typically been analysed at monthly to annual time scales and are frequently used to investigate relationships between rainfall, streamflow, storage, and groundwater dynamics (Makungo & Odiyo, 2017; Abiye et al., 2018). The blue water indices summarised in Table 2.3 therefore represent established approaches for characterising physical water availability relevant to water-resource decision-making in South Africa.

2.2.5.2 Green water indices

Green water indices represent statistical measures used to quantify soil moisture availability and evaporative processes that influence plant water use and land-atmosphere interactions (Schuol et al., 2008; Xu & Wu, 2017; Khand et al., 2021). These indices describe water stored in the soil profile, and water lost through evaporation and evapotranspiration, capturing components of the hydrological cycle that are directly relevant to vegetation growth and agricultural productivity (Schuol et al., 2008; Xu & Wu, 2017; Khand et al., 2021). In South Africa, where rain-fed agriculture dominates, and soil moisture availability strongly constrains crop and rangeland performance, green water indices provide critical insight into land-based water availability (Schuol et al., 2008).

From a decision-making perspective, green water indices are particularly important for agricultural management and drought monitoring (Mukhawana et al., 2023; Myeni et al., 2022).

Soil moisture indices, including average, minimum, and maximum soil moisture levels, provide information on the availability of water for plant uptake and can inform decisions related to planting timing, irrigation scheduling, and grazing management (Myeni et al., 2022). Soil moisture deficit and soil moisture drought indices offer interpretable measures of moisture stress relative to local conditions, supporting assessments of short-term dryness and agricultural drought risk (Mukhawana et al., 2023). Evaporation and evapotranspiration indices provide additional insight into atmospheric water demand and water losses from soils and water bodies, which are relevant for estimating irrigation requirements, managing reservoir losses, and understanding crop water use under warm and dry conditions (Jovanovic et al., 2011, 2015; Tongwane et al., 2017; Dzikiti et al., 2019).

In the South African literature, green water indices have commonly been derived from a combination of in situ observations, remote sensing products, reanalysis datasets, and hydrological or agro-hydrological model outputs (Shoko et al., 2015, 2016; Tongwane et al., 2017; Watson et al., 2022). While in situ soil moisture measurements remain spatially limited, satellite-based and modelled estimates have widely been used to characterise soil moisture variability and trends across different agroclimatic regions (Myeni et al., 2022). Evaporation and evapotranspiration indices have frequently been analysed to assess climatological patterns, evaluate satellite and reanalysis products, and investigate changes in atmospheric demand (Jovanovic et al., 2011, 2015; Tongwane et al., 2017; Dzikiti et al., 2019). These indices have typically been evaluated at monthly to annual time scales and have often been used alongside rainfall and temperature indices to assess land-surface moisture conditions. The green water indices summarised in Table 2.3 therefore represent well-established measures for characterising soil and evaporative water availability relevant to climate-sensitive decision-making in South Africa.

2.3 Review of climate databank applications and climate service principles informing the development of a climate and water availability indices app

As the impacts of climate change and variability on the physical environment and society intensify, there is an increasing need for readily accessible resources to support informed decision-making across climate-sensitive sectors. Consequently, numerous web-based tools for weather and climate information analysis, visualisation, and decision support have been developed and continue to emerge and are increasingly adopted to make weather and climate information more accessible, meaningful, and actionable (Lumley et al., 2022; VanderMolen et al., 2019). Such applications commonly function as climate databanks, providing users with access to historical, forecast, and/or projected weather and climate information through interactive interfaces that support exploration, interpretation, and application of data. Despite their growing prevalence, many of these tools, although developed with some level of end user input, sometimes lack a comprehensive evaluation of the accuracy, usability, and alignment with user needs, posing potential risks of obsolescence and limited long-term utility (Swart et al., 2017; Lumley et al., 2022; Lumbroso et al., 2024).

A central aim of WCSs is the design and delivery of information that is tailored and targeted to different decision-making contexts (Lumbroso et al., 2024). Previous studies (e.g., Hewitt et al., 2012; Lourenço et al., 2016; Lumbroso et al., 2024; VanderMolen et al., 2019) have highlighted the importance of user-centric design in the development of web-based climate databank applications and WCSs. However, these studies have shown that many applications fall short in systematically evaluating their effectiveness once deployed. This lack of comprehensive and sustained evaluation presents a potential threat to the functionality, credibility, and long-term utility of web-based WCSs. Even where tools are developed in consultation with end users and broadly align with identified needs, challenges related to navigation, usability, and interpretability are frequently reported, which can limit uptake and constrain their practical value for decision-making (Vaughan et al., 2019; Suckall & Soares, 2022).

To ensure that the Weather Risk app effectively serves its intended purpose as an operational WCSs, this review examines key principles and approaches employed in the development of comparable web-based weather and climate databank applications. In particular, the review considers how such applications are positioned within the WCSs value chain, including their roles in supporting weather and climate risk awareness, monitoring, planning, operational decision-making, and policy reporting. Attention is given to approaches for usability testing, accessibility, interface design, data presentation, and mechanisms for user engagement and feedback. Through a targeted review of the literature on web-based weather and climate applications (using search engines such as Google Scholar with keywords such as weather/climate data web app or WCSs), this study distils best practices that inform both the development and ongoing refinement of the Weather Risk app. These insights, combined with active engagement with end users, are used to assess and strengthen the alignment of the site with established WCS principles, academic standards, and the operational needs of the agricultural and water sectors, as well as other climate-sensitive sectors, in South Africa.

2.3.1 Key requirements for web-based climate tools

Historically, a significant number of web-based applications were developed as "loading docks", where climate researchers independently created information without direct input from end users (VanderMolen et al., 2019). However, this approach has since evolved towards more collaborative models, including contractual to co-produced approaches (VanderMolen et al., 2019). Consequently, researchers increasingly recognise the importance of carefully considering end users to enhance the value, relevance, and applicability of weather and climate information and services across policy, research, and decision-making contexts, even within South Africa (VanderMolen et al., 2019; Lumbroso et al., 2024).

Previous studies (e.g., McNie, 2007; Lumbroso et al., 2024) have highlighted the need for climate data and analysis tools to be appropriate to their context of application, incorporating suitable spatial and temporal scales (Dilling & Lemos, 2011; Lemos et al., 2012) and aligning with agency or organisational research and decision-making frameworks (Vogel et al., 2016, 2017). To ensure the reliability of web-based applications, they must: 1) be credible in terms of accuracy, validity, and quality; 2) maintain legitimacy through transparency; and 3) avoid bias (Cash et al., 2006; McNie, 2007). Furthermore, such applications should be comprehensible in both language and format (Dilling & Lemos, 2011). Achieving these objectives without sustained user engagement and feedback is challenging, as meaningful uptake and application depend on how well tools resonate with user needs and decision contexts (Dilling & Lemos, 2011; Lumley et al., 2022).

These principles have been synthesised from the literature to provide a structured framework for assessing and guiding the design, implementation, and evaluation of web-based WCSs. A summary of key principles to be considered when developing a web-based application is presented in Table 2.4 below, adapted from VanderMolen et al. (2019).

Table 2.4: Basic principles of web-based app development and evaluation adapted from VanderMolen et al. (2019).

Feature	Recommendation	Reference(s)
Background and content	Engage end users early; create profiles to understand their backgrounds, skills, preferences, and climate information needs and use.	Lourenço et al. (2016); Swart et al. (2017); VanderMolen et al. (2019)
	Acknowledge diversity in information needs and use; allow for creativity in the presentation and delivery of information and consider alternatives to application development where relevant.	Wall et al. (2017); VanderMolen et al. (2019)
	Perform an inventory of existing applications to avoid duplication or “portal proliferation”.	Swart et al. (2017)
	Be aware of potential preferences for “clearinghouse style” or “one-stop shop” approaches to climate applications and whether this precludes the need for the development of separate applications to present new material.	VanderMolen et al. (2019)
	Reconsider development of a site that cannot be maintained and/or sustained as content must evolve with changes in information supply and demand to remain salient.	Swart et al. (2017); VanderMolen et al. (2019)
	Provide information at a variety of spatial and temporal scales as appropriate to and informed by end user needs	Brown & Bachelet (2017); Dilling & Lemos (2011)
	Design graphics to include good colour separation and scale increments; colour should be intuitive (e.g., red indicates warm).	Brown & Bachelet (2017); VanderMolen et al. (2019)
Usability	Follow general usability guidelines in application development.	Oakley & Daudert (2016)
	Identify beforehand agency-specific software requirements that may compromise browser compatibility.	Brown & Bachelet (2017)
	Harmonize data characteristics and tools across data sources, as well as grids, colours, and formats.	Oakley and Daudert (2016); Swart et al. (2017)
	Maintain site actively (e.g., search for and fix broken links) to aid retention.	VanderMolen et al. (2019)
	Make as few overarching changes (e.g., to site structure, retrieval pathways) as possible to circumvent disruption to end users.	VanderMolen et al. (2019)
	Provide training opportunities for end users.	Brown & Bachelet (2017)
	Include an internal search function that directs end users to the desired data, tools, and information.	Swart et al. (2017)
Information resources	Offer timely, responsive help desk services, including the option to tailor or customize the data and tools present, to aid retention.	Swart et al. (2017); VanderMolen et al. (2019)
	Include clear/concise tutorials; evaluate these as well.	Oakley & Daudert (2016); Swart et al. (2017); VanderMolen et al. (2019)
	Provide cases of use to aid end users considering application of the data and tools in their own work.	Swart et al. (2017)

	Define all acronyms and concepts (e.g., consider including a glossary), explain uncertainty and provide background information (e.g., on climate models, scenarios, and station types) to aid end users in selecting the appropriate data and tools for their needs; include this information in pop-ups or hovers to reduce cognitive load.	Barsugli et al. (2013); Brown & Bachelet (2017); Oakley & Daudert (2016); VanderMolen et al. (2019)
	Avoid jargon; consider relying on a climatologist to provide accuracy and consistency in terms.	Oakley & Daudert (2016); Brown & Bachelet (2017)
	Communicate the quality of and provide clear documentation for data sources; include sample citations.	Oakley & Daudert (2016); Brown & Bachelet (2017)
Evaluation	Build an evaluation team that will enable achievement of evaluation objec-tives (e.g., a social scientist to conduct qualitative evaluation and facilitate stakeholder engagement; a climatologist to clarify terms/provide consis-tency).	VanderMolen et al. (2019)
	Conduct usability testing early with a representative sample of potential or existing end users.	Oakley & Daudert (2016)
	Choose an evaluation approach and methods that match project objectives and develop an evaluation plan that reflects the same.	Meadow et al. (2015); Wall et al. (2017); VanderMolen et al. (2019)
	Be purposive in sampling; utilize the help desk, if existent, to identify and recruit end users for evaluation.	VanderMolen et al. (2019)
	Conduct evaluation in person or via a shared screen so that interviewer and interviewee may interact over the site.	VanderMolen et al. (2019)
	Involve a diversity of end users, and create end user profiles to facilitate the following: 1) understanding of their objectives, interests and skills; 2) prescriptive determination of content, if necessary; and 3) tailoring of product and evaluation to different needs (e.g., researchers and engineers tend to access data then run their own analyses; managers tend to access data and utilize the tools provided).	Swart et al. (2017); VanderMolen et al. (2019)

2.3.2 Learning from existing web-based applications

In addition to drawing on the principles summarised in Table 2.4 and sustained engagement with end users throughout the project, it is also important to reflect on existing web-based applications that offer comparable functionality to the Weather Risk app presented under Chapter 5. Accordingly, Table 2.5 presents a non-exhaustive list of web-based applications that in part informed the design, implementation, and refinement of the Weather Risk app. The listed applications comprise interactive web-based platforms that provide accessible visual interfaces to support understanding of weather, climate, water, and/or related datasets, allowing end users to explore and dynamically generate tailored views of information. The selection of applications is guided by the definition of climate tools provided by Lumley et al. (2022), which emphasises tools that translate climate and environmental data into accessible, user-oriented information products that support understanding, monitoring, and decision-making across weather and climate-sensitive sectors. The purpose of this review is not to formally evaluate individual platforms, but rather to situate the Weather Risk app within the broader landscape of existing tools and to distil lessons from established good practice that could realistically be adopted within the constraints of available resources, capacity, and project scope.

Table 2.5: List of global, African, and South African web-based applications providing weather, climate, and/or water-related indices, used for contextual comparison with the Weather Risk application (all sites last accessed in January 2026).

Web-based app name	Description	Link to web-based app
AccuWeather	A global web-based weather application providing access to current conditions, radar and satellite visualisations, short- to medium-range forecasts, and limited historical weather information for numerous locations, including locations across South Africa, illustrating widely adopted approaches to presenting operational weather data to diverse user groups.	https://www.accuweather.com/
Africa Data Hub Climate Observer	A web-based application providing access to historical climate information for towns and cities across Africa, with a focus on observed rainfall and temperature data presented through an interactive interface to support climate awareness and basic climatological assessment.	https://www.africadatahub.org/ and https://www.africadatahub.org/data-resources/climate-observer
ARC Agricultural Drought Early Warning System (ADEWS)	A web-based application supporting the early warning and monitoring of agricultural drought across South Africa, integrating climate and environmental indicators to assess evolving drought conditions and their potential impacts on agricultural systems.	https://www.drought.agric.za/
Big Six Monitor	A South Africa-based web-based monitoring tool providing visualisation of current and historical storage levels in the major Western Cape Water Supply System dams, alongside scenario-based projections of dam storage up to 24 months ahead based on user-defined rainfall and water use assumptions.	https://cip.csag.uct.ac.za/monitoring/bigsix.html

Web-based app name	Description	Link to web-based app
CapeFarmMapper 3	A South Africa-based web-based spatial information platform providing access to climate, water, environmental, agricultural, and land-use datasets, with a strong emphasis on the Western Cape while also incorporating national-scale information. The platform offers interactive mapping tools that enable users to visualise, query, and overlay weather-, climate-, and water-related data to support agricultural planning and resource management.	https://gis.elsenburg.com/apps/cfm/
Climate Engine	A global web-based application providing interactive visualisation of climate and hydrological data through maps and time-series graphs, enabling exploration of observed and derived variables to support climate monitoring and environmental analysis.	https://www.climateengine.org/ and https://app.climateengine.org/climateEngine
Climate Information Portal	A web-based climate data portal providing access to observed and projected climate datasets for Africa, with functionality to query, visualise, and download data, alongside guidance to support appropriate interpretation and use for climate-related analysis and decision-making.	https://cip.csag.uct.ac.za/webclient2/app/
Climate Change Knowledge Portal	A global web-based platform providing access to historical and projected climate information, alongside data and insights on climate risks, vulnerabilities, impacts, and adaptation options, with functionality to explore and download country- and watershed-specific information.	https://climateknowledgeportal.worldbank.org/ and https://climateknowledgeportal.worldbank.org/country/south-africa

Web-based app name	Description	Link to web-based app
Copernicus CDS Applications	A global web-based platform hosting a suite of interactive applications developed under the Copernicus Climate Change Service to support the exploration and communication of climate information. These applications include tools for monitoring near-real-time climate conditions (Climate Pulse), visualising historical and projected climate change (Interactive Climate Atlas), exploring reanalysis data such as ERA5 (ERA Explorer), tracking global temperature trends (Global Temperature Trend Monitor), and assessing thermal stress and heat-related indicators (Thermal Trace). Together, the applications provide accessible visual interfaces for analysing weather, climate variability, extremes, and long-term change across multiple spatial and temporal scales.	https://cds.climate.copernicus.eu/applications and https://pulse.climate.copernicus.eu/ and https://atlas.climate.copernicus.eu/atlas and https://era-explorer.climate.copernicus.eu/ and https://apps.climate.copernicus.eu/global-temperature-trend-monitor/ and https://thermaltrace.climate.copernicus.eu/
ClimInonda	A global web-based application developed to integrate and visualise climate, environmental, land use, and hydrological data from multiple sources, supporting interactive exploration, trend analysis, and data download to inform environmental and water resource understanding in a basin context. Although the online deployment is currently unavailable, the app concept and functionalities provide useful insights for integrating variable types and visual analytics in climate-related platforms.	http://ec2-3-92-49-95.compute-1.amazonaws.com/ClimInonda/backend/login (currently not accessible)

Web-based app name	Description	Link to web-based app
Consortium of Universities for the Advancement of Hydrologic Science, Inc. (CUAHSI)	A global web-based data portal providing access to meteorological, groundwater, surface water, and water quality datasets, with functionality to search, visualise, plot, and export data as maps or time series for user-defined regions. The platform also allows users to upload and integrate their own geospatial datasets to support hydrological and environmental analysis.	http://data.cuahsi.org/
CropX	A web-based agronomic decision-support platform combining soil and crop data with weather observations and forecasts accessible through browser dashboards, enabling users to integrate climate and water information with farm management planning.	https://www.cropx.nl/en/
Climate System Analysis Group (CSAG) Cape Town rainfall monitor	A South Africa-based web-based monitoring platform providing near-real-time and historical rainfall information for Cape Town and its surrounding region, drawing on multiple station networks to contextualise current rainfall relative to recent years. The application offers interactive map-based station selection and visualisation of accumulated and daily rainfall time series, supporting situational awareness of regional rainfall conditions while transparently communicating data limitations.	https://cip.csag.uct.ac.za/monitoring/cta.html

Web-based app name	Description	Link to web-based app
FAO WaPOR (Water Productivity through Open access of Remotely sensed derived data)	A global web-based data platform provided by the Food and Agriculture Organization (FAO) of the United Nations that enables users to visualise and analyse remotely sensed water productivity, evapotranspiration, soil moisture, and related biophysical variables across agricultural and water-stressed landscapes. The application offers interactive maps, time-series charts, and data export functions to support decision-making on water use efficiency, irrigation planning, and climate-smart agriculture.	https://data.apps.fao.org/wapor/?lang=en
Global Surface Water Explorer	A global web-based application enabling users to explore long-term changes in surface water extent and dynamics using satellite-derived datasets, with interactive mapping tools to visualise historical patterns, seasonal variability, and trends in surface water occurrence across multiple spatial scales.	https://global-surface-water.appspot.com/ and https://global-surface-water.appspot.com/map
GreenBook	A South Africa-based web-based planning support platform providing access to downscaled baseline and future climate information, climate risk profiles, and impact insights for cities and towns, alongside interactive tools and guidance to support climate adaptation and climate-resilient development within local government planning processes.	https://greenbook.co.za/
HydroNET	A South Africa-based web-based decision-support system designed to support operational and strategic water resource management, integrating hydrological, meteorological, and water infrastructure data to enable monitoring, analysis, and decision-making related to water availability, system operations, and risk management.	https://www.hydronet.com/projects/water-control-room-south-africa/ and https://www.dws.gov.za/Projects/HydroNET/Default.aspx and https://portal.hydronet.com/login.aspx

Web-based app name	Description	Link to web-based app
iLEAF portal	A web-based weather information platform providing access to observed and forecast meteorological data from a network of weather stations across Southern Africa, including variables such as rainfall, temperature, humidity, and wind, with derived information relevant to agricultural and environmental decision-making.	https://ileaf.co.za/ and https://ileafweather.com/LogIn.aspx
INFORM Climate Change Tool	A global web-based risk assessment platform that integrates climate hazard projections with exposure, vulnerability, and population information, enabling users to explore climate change-related risk under different scenarios and time horizons through interactive dashboards, country profiles, and summary indicators.	https://drmkc.jrc.ec.europa.eu/inform-index/INFORM-Climate-Change/INFORM-Climate-Change-Tool
Intergovernmental Panel on Climate Change (IPCC) Working Group I Interactive Atlas	A global web-based application developed to support the IPCC Sixth Assessment Report, enabling spatial and temporal exploration of observed and projected climate change information. The tool summarises climate model outputs into user-selectable indicators across customisable time periods and emissions scenarios, and provides functionality to visualise, compare, and download maps, graphs, and the underlying data used in the analyses.	https://interactive-atlas.ipcc.ch/
IRI Climate Data Library	A global web-based climate data platform providing access to a wide range of observational, reanalysis, and model-based climate datasets, with functionality to subset, visualise, analyse, and download data to support climate monitoring, research, and climate services development.	https://iridl.ldeo.columbia.edu/

Web-based app name	Description	Link to web-based app
KNMI Climate Explorer	A global web-based climate analysis platform providing access to a wide range of observational, reanalysis, and climate model datasets, with tools for spatial and temporal visualisation, statistical analysis, trend assessment, and comparison across regions, variables, and time periods.	https://climexp.knmi.nl/start.cgi
Lobelia's Past Climate Explorer	A global web-based application enabling interactive visualisation of ERA5 reanalysis data through maps and time-series graphs, allowing users to explore historical climate conditions and variability across multiple variables, locations, and temporal scales.	https://era5.lobelia.earth/en/
Meteoblue	A global web-based weather and climate application providing access to observed, modelled, and forecast meteorological information, including high-resolution weather forecasts, radar and satellite visualisations, and climatological summaries for a wide range of locations, illustrating approaches for integrating weather, climate, and historical context within a single interface.	https://www.meteoblue.com/
Mzansi Amanzi	A South Africa-based web-based application providing access to historical monthly information on dam levels and catchment-scale water availability, with interactive visualisations that support retrospective assessment and comparison of water conditions across regions.	https://www.water-southafrica.co.za/
National Oceanic and Atmospheric Administration (NOAA) Climate Plotting and Analysis Tools	A global web-based suite of climate data access and analysis tools provided by NOAA, enabling users to visualise, subset, and analyse a wide range of observational, reanalysis, and climate model datasets through maps, time series, and statistical summaries.	https://psl.noaa.gov/data/getpage/

Web-based app name	Description	Link to web-based app
Norwegian Meteorological Institute YR app	A global web-based weather application operated by the Norwegian Meteorological Institute, providing location-specific weather observations, forecasts, radar and satellite visualisations, and access to historical weather information for a wide range of locations worldwide, illustrating approaches to delivering authoritative, publicly accessible operational weather services.	https://www.yr.no/
PREPdata	A global web-based application developed under the Partnership for Resilience and Preparedness (PREP) that enables spatial and temporal visualisation of climate, hazard, exposure, and socioeconomic datasets, supporting integrated exploration of climate risks and resilience-related information across regions and time periods.	https://prepdata.org/explore
South African Risk and Vulnerability Atlas (SARVA)	A South Africa-based web-based platform hosted by the South African Environmental Observation Network (SAEON) that provides access to a wide range of ecological, socioeconomic, settlement, climate, and water-related datasets sourced from multiple organisations. The platform supports visualisation and exploration of historical and future climate information, including mean conditions and climate indices, as well as water availability data, through a suite of interactive decision-support applications, including risk mapping and climate risk tools that summarise projected changes for near-, mid-, and far-future periods.	https://sarva.saeon.ac.za/ and https://gisportal.saeon.ac.za/portal/apps/webappviewer/index.html?id=2d572dcf9c5f47c484540f8c934e03f4# and https://sarvamaps.saeon.ac.za/climate-tool/

Web-based app name	Description	Link to web-based app
SAWS WCS products	A South Africa-based suite of web-based weather and climate service products providing access to observed and forecast meteorological information, climate summaries, and early warning products at national and regional scales. These services support monitoring and communication of weather conditions, climate variability, and climate-related risks across multiple sectors, including agriculture, water management, disaster risk reduction, and public safety.	https://www.weathersa.co.za/home/
TerraClim products	A South Africa-based suite of web-accessible climate data products and tools providing high-resolution historical and near-real-time weather and climate information at national scale. TerraClim products support the visualisation, access, and use of temperature, rainfall, water balance variables, and derived climate indices relevant to South African environmental and agricultural applications.	https://www.terraclim.com/tools
Ventusky	A global web-based weather application providing interactive visualisation of current and forecast meteorological conditions through dynamic, layered maps and animations. Users can explore a range of variables, including wind, temperature, precipitation, pressure, clouds, and more, at different altitudes and timeframes to assess evolving weather patterns around the world.	https://www.ventusky.com/
Weather & Radar	A global web-based weather application providing interactive access to current conditions, precipitation radar, satellite imagery, and short- to medium-range forecasts, illustrating radar-focused approaches to visualising and communicating evolving weather systems.	https://www.weatherandradar.com/

Web-based app name	Description	Link to web-based app
Western Cape Government Weather Station Portal	A provincial web-based portal providing access to observed weather station data for the Western Cape Province of South Africa, with functionality to view hourly, daily, and monthly meteorological information as tables, graphs, or summary outputs, and to export data for further analysis.	https://gis.elsenburg.com/apps/wsp/#
Windguru	A global web-based weather application providing current conditions and multi-day forecast information for a wide range of meteorological variables, with a strong emphasis on wind and wave parameters presented through tabular, time-series, and location-specific forecast outputs.	https://www.windguru.cz/
Windy	A global web- and mobile-based weather application providing interactive visualisation of both current and forecast meteorological conditions across a wide range of variables, including wind, temperature, precipitation, clouds, pressure, humidity, waves, and atmospheric composition. The platform allows users to explore layered, animated map fields and location-specific views to assess evolving weather conditions across multiple spatial and temporal scales.	https://www.windy.com/
Zoom Earth	A global web-based weather and earth observation application that provides near-real-time satellite imagery and animated visualisations of weather systems and environmental conditions, along with current weather observations and radar data, enabling users to explore evolving atmospheric and surface features at multiple spatial scales.	https://zoom.earth/

A total of 37 web-based tools were explored, noting that several entries represent collections or suites of related applications rather than single platforms (Table 2.5). Each application was browsed to understand how weather-, climate-, water-, and risk-related information is presented to users, and to contextualise the design and functionality of the completed Weather Risk app within the broader landscape of existing tools.

Across many platforms (e.g., Africa Data Hub Climate Observer, Climate Engine, and the IPCC Working Group I Interactive Atlas), an introductory landing or information page is provided prior to accessing the core application, allowing users to familiarise themselves with the scope and purpose of the tool. In contrast, several applications require user registration before full access is granted (e.g., ADEWS and HydroNET), while others offer a "guest mode" that enables users to explore functionality without registration (e.g., Climate Information Portal, CUAHSI, and Windy). As noted by Ali et al. (2023), guest access can play an important role in allowing potential users to visualise an application and explore its functionality before committing to registration. Some applications (e.g., the IPCC Interactive Atlas and selected CDS applications) provide unrestricted access without registration, with all features immediately available. Where registration is required, especially after the "guest mode" access, additional functionality and personalised features are often unlocked. Beyond access control, registration also provides an important mechanism for maintaining a user database and facilitating ongoing feedback, which is critical for iterative improvement of these web-based tools (de Amorim et al., 2020; Ali et al., 2023). User feedback is widely recognised as an essential component of application development and long-term usability (Brown & Bachelet, 2017), and many of the reviewed platforms provide options for users to submit feedback or contact developers. While such mechanisms differ from structured user surveys, they nevertheless enable continuous engagement with users. These principles have been incorporated into the operational Weather Risk app through structured user engagement activities, with additional mechanisms for ongoing user feedback being implemented.

In terms of supporting user uptake and navigation, several applications provide additional guidance through demo requests (e.g., SARVA), instructional videos (e.g., Climate Engine and the IPCC Interactive Atlas), guided tours (e.g., Climate Engine), or detailed user manuals (e.g., CapeFarmMapper3). Such features are recognised as important for enabling users to gain a full understanding of application functionality, particularly for platforms with complex datasets and analytical options (Brown & Bachelet, 2017). Once accessed, most applications provide an interactive map as the primary landing interface, used either to visualise gridded datasets or to display the locations and attributes of point-based station data (e.g., ADEWS). Many platforms also allow users to generate graphs and query data dynamically (e.g., Climate Engine and the IPCC Interactive Atlas), including the ability to customise time periods, seasons, or spatial domains. The presentation of information is a critical design consideration, with intuitive and consistent colour schemes (e.g., colour ramps aligned with the physical meaning of variables such as temperature or rainfall) supporting interpretation and usability (Brown & Bachelet, 2017; Lumley et al., 2022). The importance of user feedback in refining visual design and interpretability is evident across the reviewed tools, and the Weather Risk app has been designed to support ongoing user feedback and iterative refinement to improve usability and clarity over time.

A further common feature across many applications is the provision of clear information on available datasets, including data sources, descriptions, interpretation guidance, and metadata, often delivered through hover-over pop-ups or contextual information panels. However, the literature emphasises that such descriptions should avoid unnecessary scientific jargon and instead be communicated in a user-friendly manner (Brown & Bachelet, 2017; Hewitson et al., 2017; Lumley et al., 2022). Within the reviewed tools, only a subset, most notably the IPCC Interactive Atlas among others, presents climate information predominantly in the form of indices that extend beyond mean conditions. Explicit communication of data uncertainty is also increasingly recognised as an important component of web-based climate tools (Lumley et al., 2022). At the same time, Brown & Bachelet (2017) note that users place value on information that links climate signals to potential impacts, enabling them to better interpret and apply the information in practice. These considerations have been addressed within the Weather Risk app through the inclusion of explanatory information for variables and indices, alongside practical interpretation guidance, all to be improved in subsequent updates.

For applications hosting large numbers of datasets and features, search functionality is commonly provided (e.g., Climate Engine, Climate Information Portal, and SARVA), facilitating efficient navigation. Data export functionality is also widely supported, ranging from simple screenshot capture to the export of maps and graphs (e.g., IPCC Interactive Atlas), and in some cases, the download of underlying datasets used to generate visualisations (e.g., NOAA Climate Plotting and Analysis Tools). Where data export is provided, compatibility with commonly used software environments such as QGIS and spreadsheet applications is an important consideration. In addition, some platforms allow users to upload their own datasets for analysis within the application environment (e.g., ClimInonda), highlighting the value of flexible data integration. In such cases, clear guidance on data formats and example inputs is essential. Finally, a subset of applications provides tailored messages or summaries to support the interpretation and application of information (e.g., ADEWS), illustrating approaches for translating data outputs into more decision-relevant insights.

2.4 Synthesis and key insights for operational climate services

This chapter reviewed rainfall- and temperature-based climate indices together with selected water availability indices, alongside key weather and climate service principles and existing web-based climate databank applications, to support the development of an operational weather and climate information platform for South Africa. The review was intentionally targeted rather than exhaustive, focusing on scientifically robust indices, widely applied in the South African literature, and suitable for consistent derivation from observational and gridded datasets at the national scale.

Across rainfall, temperature, and water availability domains, a consistent set of index groupings emerged that reflect both common practice in the literature and practical relevance for decision-making. Rainfall indices describing seasonality, average conditions, extremes, and dry spells were shown to provide complementary perspectives on rainfall behaviour, capturing not only total amounts but also timing, persistence, and variability that are critical for agricultural and water-resource applications. Temperature indices similarly extend beyond mean conditions to describe seasonality, hot and cold extremes, and event persistence, offering interpretable measures that align closely with crop growth processes, livestock stress, water demand, and risk management. Water availability indices further link atmospheric conditions to surface and subsurface water resources, providing essential context for understanding hydrological responses and constraints in a water-scarce environment.

A key insight from the review is that indices are most useful for decision-making when they translate complex weather, climate, and hydrological information into impact-relevant characteristics that resonate with user needs. Indices describing thresholds, durations, and frequencies, such as growing season length, dry spell persistence, heatwave characteristics, and streamflow or soil moisture anomalies, provide intuitive and actionable information that is often more meaningful to stakeholders than raw variables alone. At the same time, baseline indices describing average conditions remain essential for contextualising extremes, supporting seasonal planning, and enabling longer-term climate risk assessment.

The review of existing climate databank applications and WCS principles highlights that the value of indices depends not only on their scientific validity but also on how they are delivered to users. Effective operational WCSs require platforms that are credible, transparent, accessible, and user-centred, with clear guidance on interpretation, uncertainty, and appropriate use. Lessons drawn from established global and South African tools emphasise the importance of intuitive interfaces, consistent visual design, explanatory support, and mechanisms for user feedback and evaluation to sustain relevance and uptake over time.

Taken together, this chapter provides a defensible foundation for the selection and operationalisation of indices within the Weather Risk app. While rainfall-, temperature-, and water availability-based indices form the core focus of this review, they are recognised as part of a broader suite of variables and derived indicators required to support comprehensive WCSs. Additional meteorological, land-surface, and impact-relevant variables, and indices derived from them, are necessary to fully capture compound risks, sector-specific sensitivities, and evolving decision-making needs. By integrating a core, well-established set of indices with the flexibility to incorporate additional variables and indicators over time, the Weather Risk app is positioned to deliver weather and climate information that is both scientifically grounded and operationally responsive. This synthesis establishes a clear bridge between the academic literature, operational WCS design, and the decision-making needs of weather- and climate-sensitive sectors in South Africa, particularly agriculture and water resource management.

Chapter 3: Application and evaluation of climate indices across datasets

3.1 Introduction

This chapter addresses Objective 2 of the project, which aims to evaluate selected gridded climate datasets and to demonstrate, through illustrative case studies, the computation and application of rainfall- and temperature-based climate indices relevant to the South African context. The focus is on the use of climate indices to characterise climate variability, temporal trends, and extremes, and to explore their potential linkages with agriculturally relevant indicators such as crop production and livestock numbers.

Through a series of case studies, the chapter examines the behaviour and performance of climate indices derived from both weather station observations and gridded climate products, including ERA5 and datasets derived from ERA5. These applications illustrate how different data sources influence index estimates, how indices respond across spatial and temporal scales, and what limitations may arise when gridded datasets are used for climate impact assessment and decision-support applications in South Africa.

The analyses presented in this chapter are framed as independent, applied investigations rather than as a methodological precursor to the development of the Weather Risk app. While many of the indices examined here are also utilised elsewhere in the project, the purpose of this chapter is to demonstrate, in practice, which types of datasets are suitable for calculating selected indices, how results vary depending on data source and methodological choices, and how indices can be interpreted in relation to both climatic extremes and sector-relevant impacts.

The chapter presents a range of case studies covering: 1) linkages between climate indices and agricultural indicators; 2) the evaluation of gridded rainfall datasets for heavy rainfall indices and extreme low temperature event (ELTEs) indices; 3) spatial and temporal characteristics of precipitation over a key water management region; and 4) the assessment of temperature-based indices associated with ELTEs. Collectively, these case studies draw on a combination of postgraduate research undertaken within the scope of the project and analyses conducted by the project team, and are synthesised to highlight common findings and practical limitations of climate index applications in South Africa, while providing a bridge to subsequent chapters focused on the operational delivery of weather information and derived indices through the Weather Risk app.

3.2 Case study one: linking climate indices to crop and livestock statistics

3.2.1 Introduction

Weather conditions experienced over the course of a growing or production season play a critical role in shaping agricultural output across South Africa (Zinyengere et al., 2013; Archer et al., 2021; Bradshaw et al., 2022). Seasonal rainfall characteristics, temperature extremes, and atmospheric demand influence crop growth, yield formation, and livestock performance, often through cumulative and interacting processes rather than through individual daily events (Archer et al., 2021; Bradshaw et al., 2022). As a result, understanding how seasonal climatic conditions relate to agricultural outcomes is central to climate-informed agricultural decision-making.

To date, much of the research linking climate and agriculture in South Africa has focused on crop systems, with analyses typically based on raw climate variables, such as seasonal rainfall totals or mean temperatures (Moeletsi, 2017; Masupha & Moeletsi, 2018; Olabanji et al., 2020). While this work has provided valuable insights, it often overlooks the added interpretability offered by climate indices, which integrate weather information into metrics that more directly reflect agricultural stressors and conditions. Furthermore, comparatively few studies have examined climate-agriculture relationships for livestock systems, despite their sensitivity to thermal stress, water availability, and seasonal climate variability.

This case study, led by Dr S Roffe, contributes to addressing these gaps by illustrating how selected weather and climate indices can be linked to both crop and livestock statistics within a consistent analytical framework. The work contributes directly to Objective 2 of the project by demonstrating the computation and application of rainfall-, temperature-, and water-related indices in an agricultural context. Rather than seeking to identify optimal indices or define production thresholds, the analysis is deliberately illustrative, focusing on how indices can be used to contextualise agricultural variability using information available through the Weather Risk app.

Two contrasting agricultural systems are examined, namely cattle production in the Thabazimbi district in Limpopo Province and maize production in the Koppies district in the Free State Province. These locations were randomly selected based on the Department of Agriculture's (DoA) major agricultural types dataset (Waldner et al., 2017), which identifies livestock as the dominant agricultural activity in Thabazimbi and grain production as dominant in Koppies. Together, the case studies demonstrate how climate indices, beyond simple rainfall totals or temperature averages, can provide a more nuanced representation of seasonal conditions relevant to different agricultural commodities, and how such information could support climate-aware agricultural decision-making.

3.2.2 Data and methodology

Two case studies are presented to illustrate the application of climate indices to contrasting agricultural systems in South Africa, namely livestock production in the Thabazimbi district in Limpopo Province and maize production in the Koppies district in the Free State Province. As already mentioned, the selection of these case studies is informed by the DoA's major agricultural types dataset (Waldner et al., 2017), which identifies livestock and grain production as the dominant agricultural activities in the respective districts. Although the overall analytical framework is consistent across both case studies, the data sources and processing steps differ in accordance with the nature of the agricultural systems considered. As such, the data and methodological approach are described separately for each case study below, with emphasis placed on highlighting how seasonal climate indices derived from weather observations were examined alongside agricultural statistics to illustrate the potential value of climatic indices within a decision-support context.

In both case studies, the climate indices considered correspond to indices available through the Weather Risk app (see Section 5.3.2), which provides index values at a daily time step and updates them operationally in near real time. For this analysis, the indices were aggregated to seasonal summer and/or winter summaries to align with the annual temporal resolution of the available livestock and crop statistics. This approach enables a direct comparison between seasonal climate conditions and interannual agricultural outcomes, while retaining the interpretability of the indices that farmers would encounter through the Weather Risk app.

The livestock case study focuses on cattle production in the Thabazimbi district. Annual magisterial district-level cattle census data (i.e., annual number of cattle) were obtained from the DoA and are based on farmer surveys conducted at the district level, covering the period from August 2001 to August 2023. Climate data for the Thabazimbi area were obtained from quality-controlled weather station observations provided by the ARC and are available at a daily temporal resolution from 2003 to the present (Moeletsi et al., 2022). The overlapping period between the agricultural and climate datasets was used in the analysis. To emphasise interannual variability in cattle numbers, the livestock data were expressed as the annual percentage rate of change, calculated relative to the previous year. This transformation was applied to reduce the influence of longer-term, non-climatic drivers of change, such as shifts in land tenure, subsidies or trade policies, changes in livestock management practices, or broader economic development (Dean & Macdonald, 1994). The resulting time series, therefore, provides an indicative measure of short-term variability that may be more directly related to seasonal climatic conditions. Seasonal climate indices were computed for both summer (December-February) and winter (June-August), focusing on average minimum and maximum temperature-based metrics (Tn and Tx, respectively) and the temperature-humidity index (THI), which integrates air temperature and relative humidity to provide an indicator of potential thermal stress in livestock (Garry et al., 2021). THI and temperature metrics were selected for this case study due to the sensitivity of livestock to thermal stress and the predominantly warm to hot climatic conditions that characterise the Thabazimbi region (Roffe & van der Walt, 2023). All indices were used in their raw form, without further transformation, to reflect the values available to users of the Weather Risk app.

The crop case study examines maize production in the Koppies district. Annual magistrate-level maize yield data (tons), collected by the National DoA through farmer reporting, have been available for 1980/81-2024/25, with maize yields reported at a yearly scale for each summer growing season, with planting from roughly October to December and harvesting in April/May. Climate data for the Koppies area were obtained from quality-controlled weather station observations provided by the ARC and are available at a daily temporal resolution from 2000 to the present (Moeletsi et al., 2022). The overlapping period of 2000/01-2024/25 between the agricultural and climate datasets was used in the analysis. To focus on short-term yield variability, the maize yield time series was detrended by removing a fitted linear trend (using ordinary least squares regression of yield against time), and subsequently normalised using z-score standardization by subtracting the mean and dividing by the standard deviation (Masupha & Moeletsi, 2018). Detrending was applied to reduce the influence of non-climatic drivers of long-term change, including improvements in seed varieties, increased fertiliser and pesticide use, and mechanization, while normalisation was used to facilitate comparison across years by placing yield anomalies on a consistent scale (Masupha & Moeletsi, 2018). Climate indices for Koppies were computed for the summer (December-February) season, corresponding to the mid-season of the maize growing period (Moeletsi & Walker, 2012). The indices included rainfall-, potential evapotranspiration- (PET), and temperature-based metrics, expressed as seasonal Tn and Tx values. These indices were selected for this case study, given the sensitivity of maize to heat stress, water availability, and atmospheric water demand during the summer growing season (Moeletsi & Walker, 2012; Bradshaw et al., 2022; Chemura et al., 2022; Simanjuntak et al., 2023). As with the livestock case study, the climate indices were analysed in their raw form to ensure consistency with the values presented within the Weather Risk app.

For both case studies, two complementary analytical approaches were applied. First, boxplots were constructed to compare the distributions of selected climate indices between years characterised by positive and negative agricultural outcomes, defined as either positive or negative rates of change in cattle numbers or positive or negative detrended, normalised maize yield. This approach provides a simple visual assessment of whether climatic conditions differ systematically between relatively favourable and unfavourable agricultural years. Second, scatter plots were used to examine the relationship between individual climate indices and agricultural outcomes. Spearman's rank correlation coefficient (ρ) and the associated p-value (statistical significance at 5% alpha level) were calculated for each index to provide a non-parametric measure of association. These analyses are intended to be illustrative rather than inferential, highlighting potential relationships and limitations rather than establishing causality.

3.2.3 Results and discussion

The results presented below illustrate how weather and climate indices, as conceptualised within the Weather Risk application (see Section 5.3.2), can be used to contextualise interannual variability in agricultural outcomes for both livestock and crop systems. While the Weather Risk app provides these indices at a daily time step and updates them operationally in near-real-time, the analyses presented here aggregate selected indices over seasonal periods to enable comparison with annually reported livestock and crop statistics. This aggregation does not alter the underlying meaning or intended interpretation of the indices but rather aligns the temporal scale of the climate information with that of the available agricultural data. As such, the case studies demonstrate the potential value of the same daily indices available through the Weather Risk app when considered cumulatively over a season, reflecting how farmers may retrospectively assess seasonal conditions or monitor the evolving progression of a season using the platform.

3.2.3.1 Livestock case study: Cattle in the Thabazimbi District

The livestock case study examines the relationship between seasonal thermal conditions and interannual variability in cattle numbers for the Thabazimbi district in Limpopo Province. Results are presented using boxplots and scatter plots to compare selected temperature- and THI-based indices between years with positive and negative rates of change in cattle numbers, and to assess the direction and strength of monotonic relationships between these indices and cattle population change. The analysis is intended to illustrate the potential value of climate indices for contextualising livestock outcomes, rather than to establish causal thresholds or predictive relationships.

Figure 3.1 presents boxplots of selected summer (December-February) temperature and THI indices for years characterised by positive and negative rates of change in cattle numbers in the Thabazimbi district. Across most indices, years associated with negative cattle population change typically exhibited higher summer temperatures and THI values compared to years with positive change, such that years with hotter (cooler) conditions more consistently occurred during years of reduced (increased) cattle populations (Figure 3.1). This pattern is particularly evident for indices describing extreme heat conditions, such as maximum temperature and the 10-day hottest temperature metrics, as well as for both mean and maximum THI (Figure 3.1). Although there is overlap between the distributions, the overall tendency toward warmer and more thermally stressful summer conditions during negative outcome years suggests that elevated heat load during summer may contribute to short-term variability in cattle numbers (Figure 3.1).

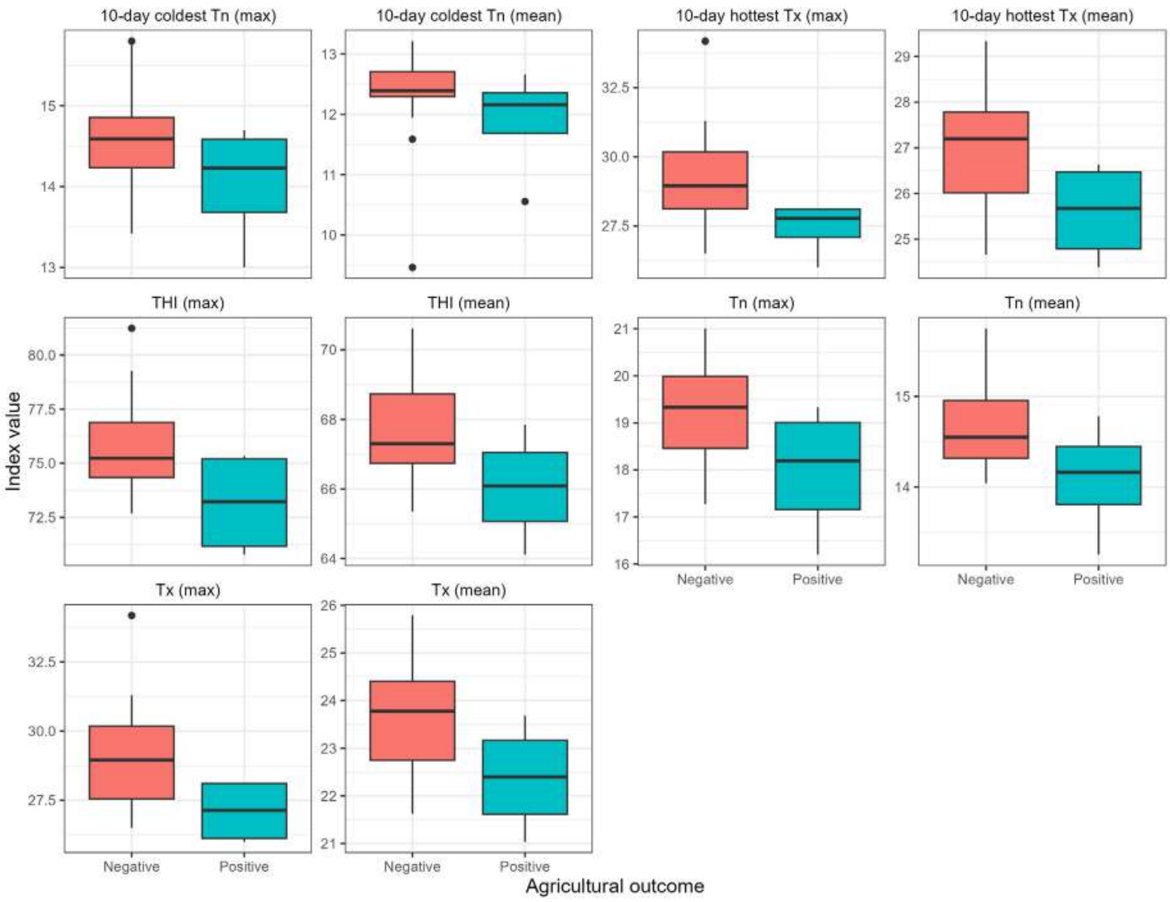

Figure 3.1: Boxplots of selected summer (December-February) temperature and temperature-humidity Index (THI) indices for years with positive and negative rates of change in cattle numbers (i.e., agricultural outcome) for the Thabazimbi district.

The scatter plots and correlation analysis further support this interpretation (Figure 3.2). All summer (December-February) temperature and THI indices exhibited negative Spearman rank correlations with the annual rate of change in cattle numbers, indicating a consistent tendency for higher thermal conditions to be associated with reduced cattle population growth (Figure 3.2). Although only one of the ten indices (i.e., the seasonal maximum daily minimum temperature, namely Tn max) was characterised by a statistically significant correlation ($\rho = -0.47$, $p = 0.043$), the direction of association is consistent across all indices (Figure 3.2). Collectively, these results suggest that years with positive rates of cattle population change were generally associated with lower summer temperatures and reduced heat stress, reinforcing the importance of monitoring thermal conditions during the summer season. While statistical significance is limited by sample size and the influence of non-climatic drivers, the coherence of the signal across multiple indices highlights the value of temperature- and THI-based indices for contextualising livestock outcomes, as operationalised within the Weather Risk app.

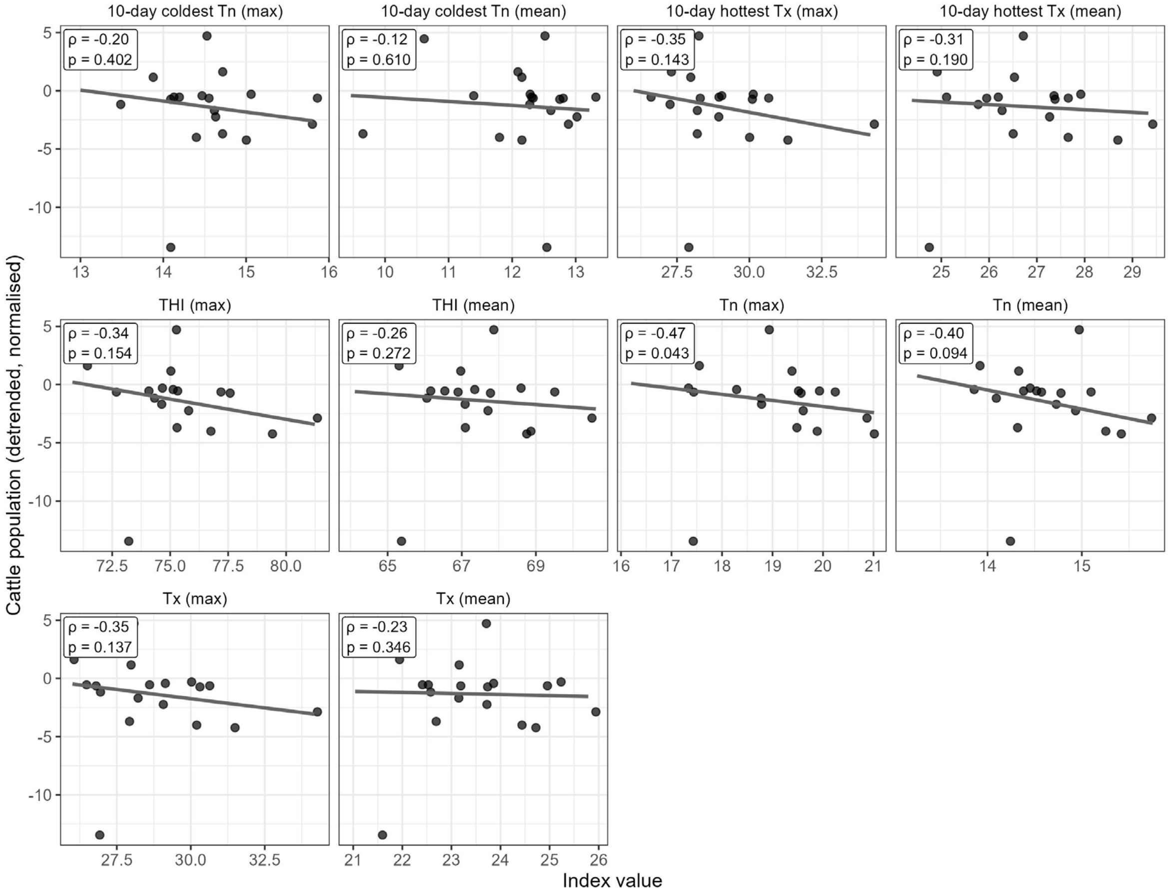

Figure 3.2: Scatter plots showing the relationship between selected summer (December–February) temperature and temperature-humidity index (THI) indices (x-axis) and cattle population rate of change (y-axis) for the Thabazimbi district. Each point represents a single summer season for a given year, pairing the climate index value with the corresponding cattle population rate of change. Spearman's rank correlation coefficient (ρ) and associated p-value are shown for each index.

Winter (June-August) results display a contrasting pattern in many, but not all, instances (Figure 3.3). Boxplots of temperature and THI indices for June-August indicate that, in general, years with positive rates of change in cattle numbers were associated with milder winter conditions, including warmer minimum temperatures and slightly elevated THI values (Figure 3.3). However, this pattern is not uniform across all indices (Figure 3.3). Years with negative cattle population change typically coincided with colder winter conditions, particularly lower night-time temperatures, although some overlap between the two outcome groups is evident (Figure 3.3). These patterns are broadly consistent with the sensitivity of livestock to cold stress, especially in regions where winter temperatures can periodically drop to levels that affect animal health and condition.

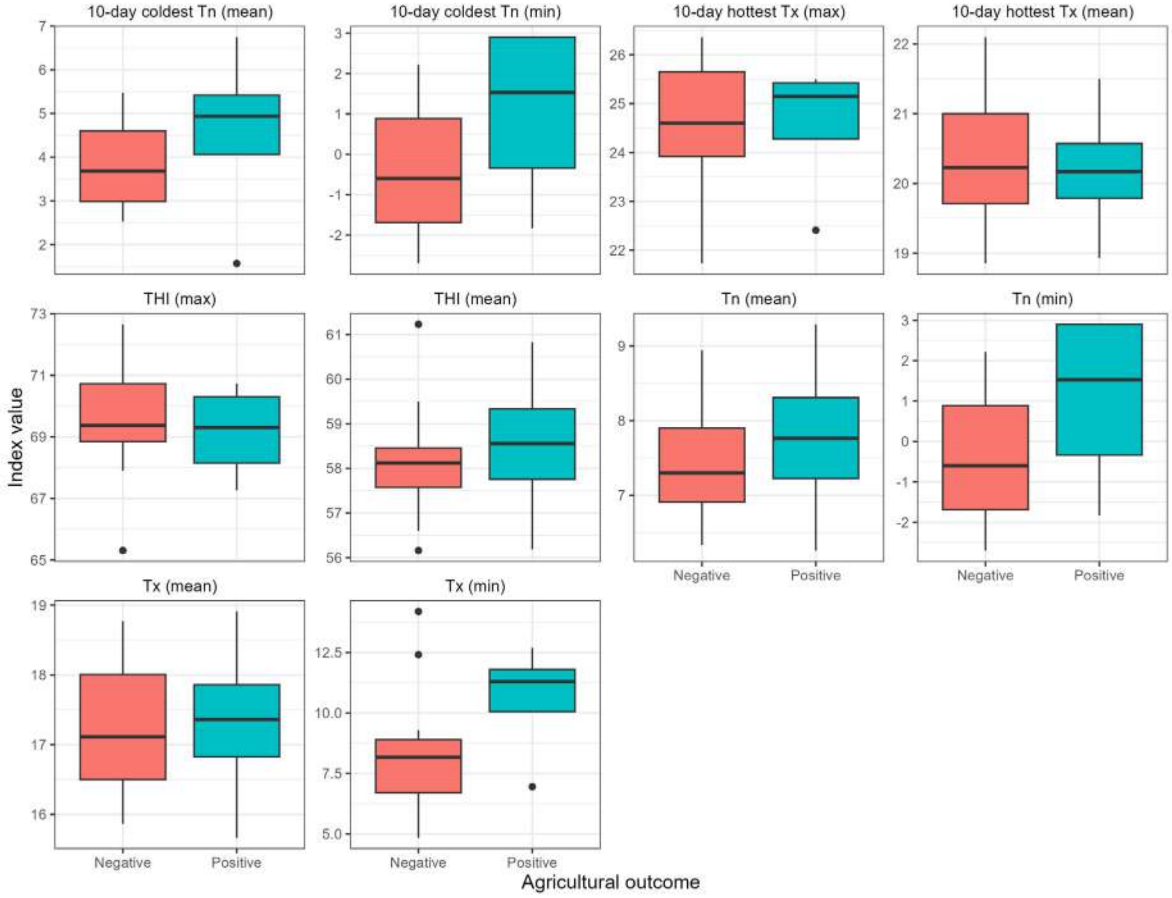

Figure 3.3: Boxplots of selected winter (June-August) temperature and temperature-humidity Index (THI) indices for years with positive and negative rates of change in cattle numbers (i.e., agricultural outcome) for the Thabazimbi district.

Scatter plots for the June-August season show predominantly positive, though generally weak, correlations between winter temperature or THI indices and cattle population rate of change (Figure 3.4). All but one of the indices exhibit positive associations, with the seasonal mean daily maximum temperature (Tx mean) being the only index characterised by a negative relationship, while none of the correlations were statistically significant (Figure 3.4). Together, these results suggest that relatively warmer winters were associated with short-term cattle population stability or growth in some years, although winter thermal conditions alone do not consistently explain interannual variability in cattle numbers. The generally weak relationships likely reflect the complex interplay between climatic and management factors during the winter period, including supplementary feeding, shelter, and herd management practices. The consistent patterns across the indices again reflect value in the inclusion of temperature and thermal comfort indices within the Weather Risk app (Figure 3.4).

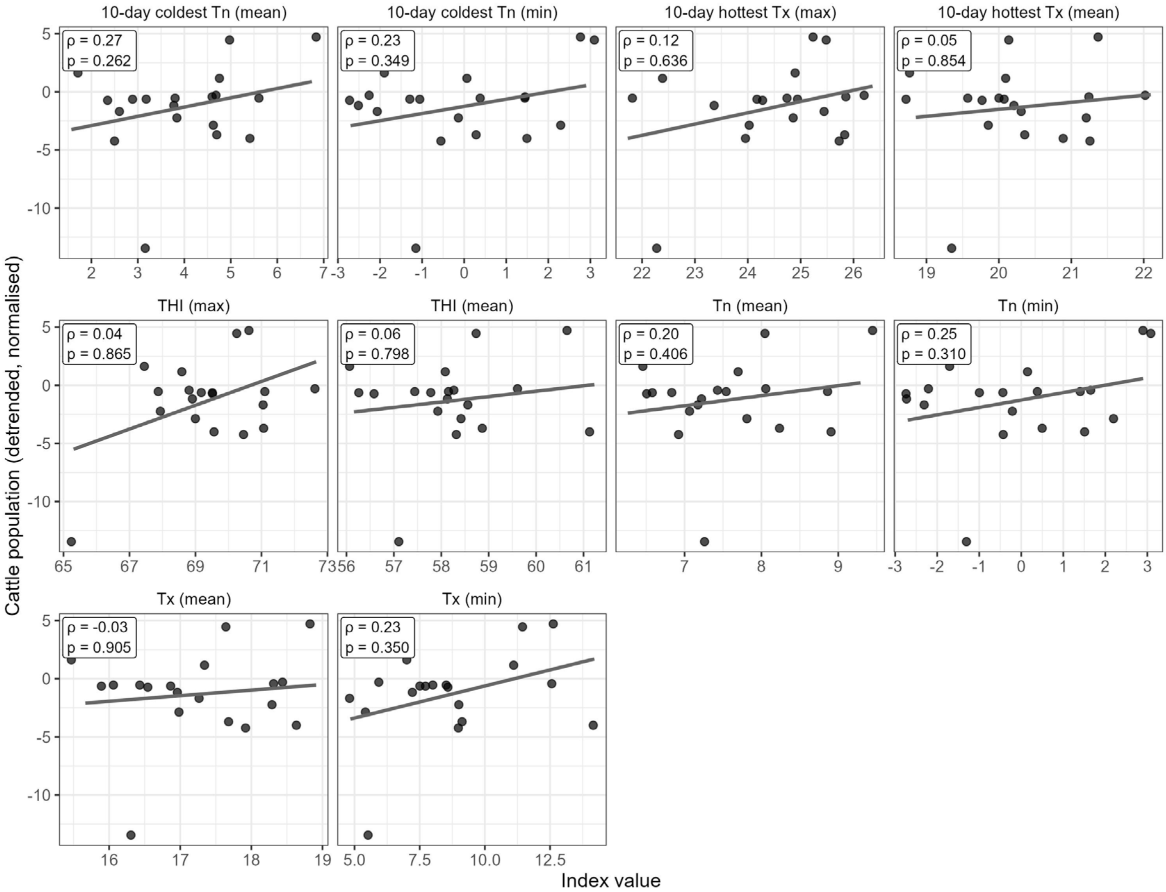

Figure 3.4: Scatter plots showing the relationship between selected winter (June-August) temperature and temperature-humidity Index (THI) indices (x-axis) and cattle population rate of change (y-axis) for the Thabazimbi district. Each point represents a single winter season for a given year, pairing the climate index value with the corresponding cattle population rate of change. Spearman's rank correlation coefficient (ρ) and associated p-value are shown for each index.

Taken together, the livestock case study illustrates how climate indices can be used to provide meaningful context for interannual variability in cattle numbers. Seasonal temperature and THI indices capture aspects of thermal stress that align with periods of livestock decline or growth, particularly highlighting the role of summer heat stress and, to a lesser extent, winter cold conditions. Importantly, the results underscore the value of presenting climate information in the form of interpretable indices that can be explored alongside agricultural statistics, rather than relying solely on seasonal averages or totals. Within an operational platform such as the Weather Risk app, these indices offer a practical means for livestock farmers and advisors to assess seasonal climate conditions that may influence herd performance and management decisions.

3.2.3.2 Crop case study: Maize in the Koppies district

The maize case study examined the relationship between summer (December-February) climate conditions and interannual variability in maize yield for the Koppies district in the Free State Province. Results are presented using boxplots and scatter plots to compare selected rainfall-, PET-, and temperature-based indices between years with positive and negative detrended, normalised maize yield, and to assess the direction and strength of monotonic relationships between these indices and yield variability. As with the livestock case study, the analysis is intended to illustrate the potential value of climate indices for contextualising crop yield outcomes, rather than identifying causal thresholds or establishing predictive relationships. By summarising daily weather observations into indices that capture key agroclimatic stressors relevant to maize production, this analysis reflects the type of information made available through the Weather Risk app. Although the analysis is conducted at a seasonal scale, the indices correspond to those operationally produced and updated daily within the platform, providing an illustrative example of how index-based information could be used by farmers and advisors to interpret prevailing or recent climatic conditions in relation to observed yield outcomes.

Figures 3.5 to 3.8 present the relationship between summer (December-February) climate indices and detrended, normalised maize yield for the Koppies district. The boxplots of rainfall- and PET-related indices indicate that years with positive maize yield anomalies were generally associated with wetter summer conditions, including higher seasonal rainfall totals, more frequent rain days, and lower atmospheric water demand as reflected by PET-related indices (Figure 3.5). In contrast, years with negative maize yield anomalies typically coincided with drier conditions and elevated PET values, suggesting increased moisture stress during the growing season (Figure 3.5). Although there is overlap between the distributions, the separation between positive and negative yield years is evident for several rainfall and PET indices, highlighting their relevance for maize production (Figure 3.5).

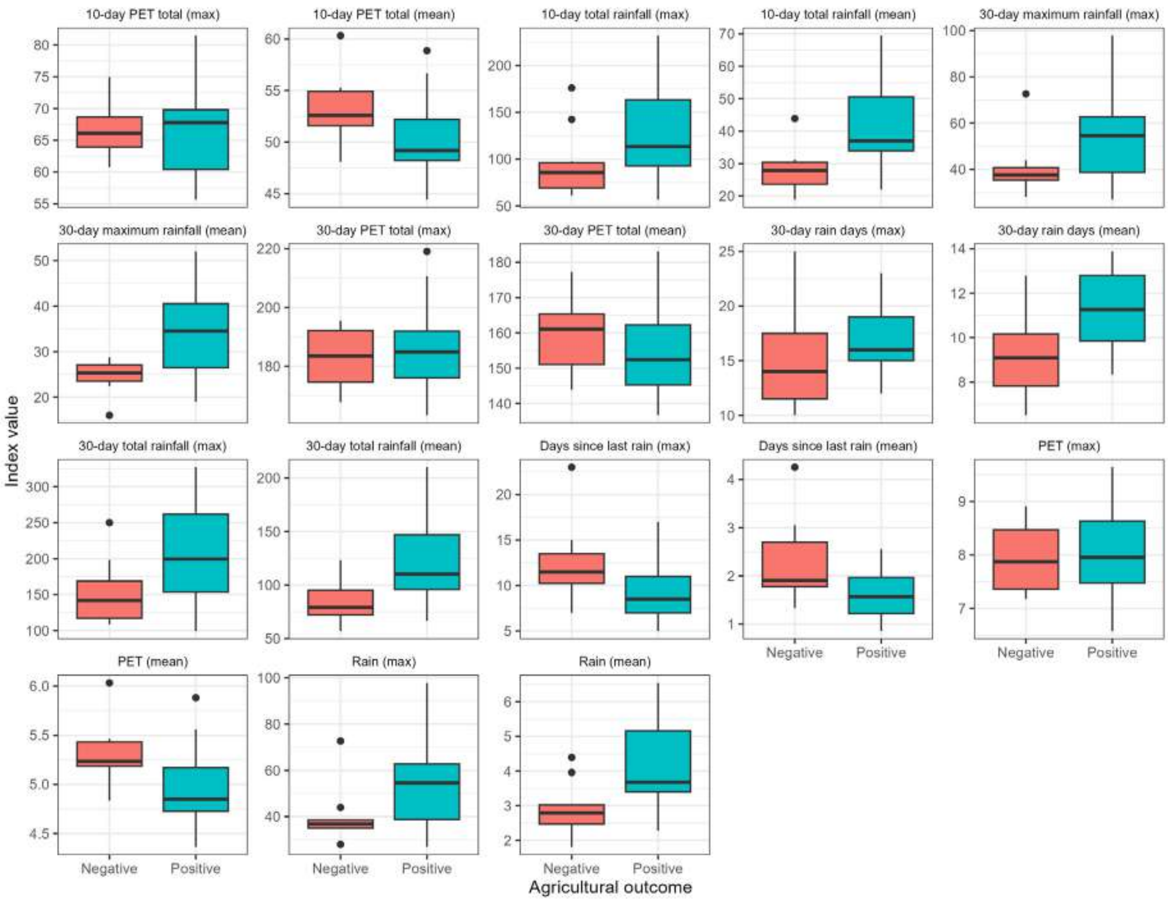

Figure 3.5: Boxplots of selected summer (December-February) rainfall- and potential evapotranspiration (PET)-related indices for maize for the Koppies district, grouped by years with positive and negative detrended, normalised maize yield.

Scatter plots for rainfall- and PET-related indices further support these patterns, with several indices exhibiting moderate correlations with detrended maize yield (Figure 3.6). A substantial proportion of the rainfall and PET indices are characterised by statistically significant relationships, with 12 out of 18 indices showing significant Spearman rank correlations (Figure 3.6). Overall, higher rainfall totals, more frequent rainfall events, and shorter dry spells were associated with higher maize yields, while higher PET values were associated with reduced yields (Figure 3.6). Although the strength of individual relationships varies across indices, the consistency in the direction of these associations indicates that summer moisture availability and atmospheric water demand play an important role in driving interannual variability in maize yields at Koppies (Figure 3.6). These results underscore the value of including rainfall- and PET-based indices within the Weather Risk app, as they capture key agroclimatic stressors that are closely aligned with observed yield variability during the growing season.

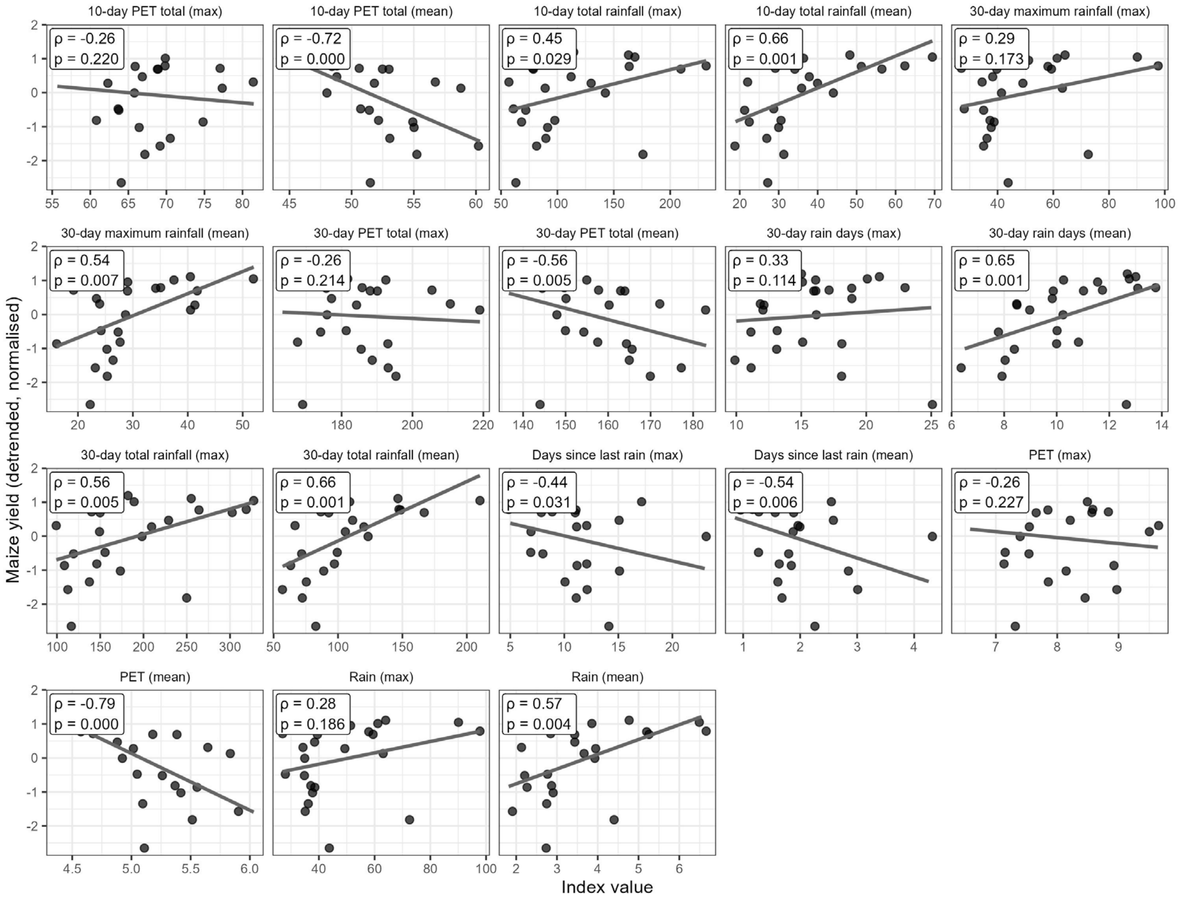

Figure 3.6: Scatter plots showing the relationship between selected summer (December-February) rainfall- and potential evapotranspiration (PET)-related indices (x-axis) and detrended, normalised maize yield (y-axis) for the Koppies district. Each point represents a single summer season for a given year, pairing the climate index value with the corresponding detrended, normalised maize yield. Spearman's rank correlation coefficient (ρ) and associated p-value are shown for each index.

Boxplots of temperature-related indices show a nuanced response (Figure 3.7). Years with positive maize yield anomalies were associated with lower summer Tn and Tx values, while years with negative yield anomalies typically coincided with higher values of both indices (Figure 3.7). This pattern suggests that elevated day- and night-time temperatures may contribute to yield reductions, particularly during sensitive growth stages. However, the separation between the two outcome groups is less pronounced than for rainfall- and PET-related indices, indicating that temperature acts primarily as a compounding stressor rather than the dominant driver of interannual yield variability at Koppies.

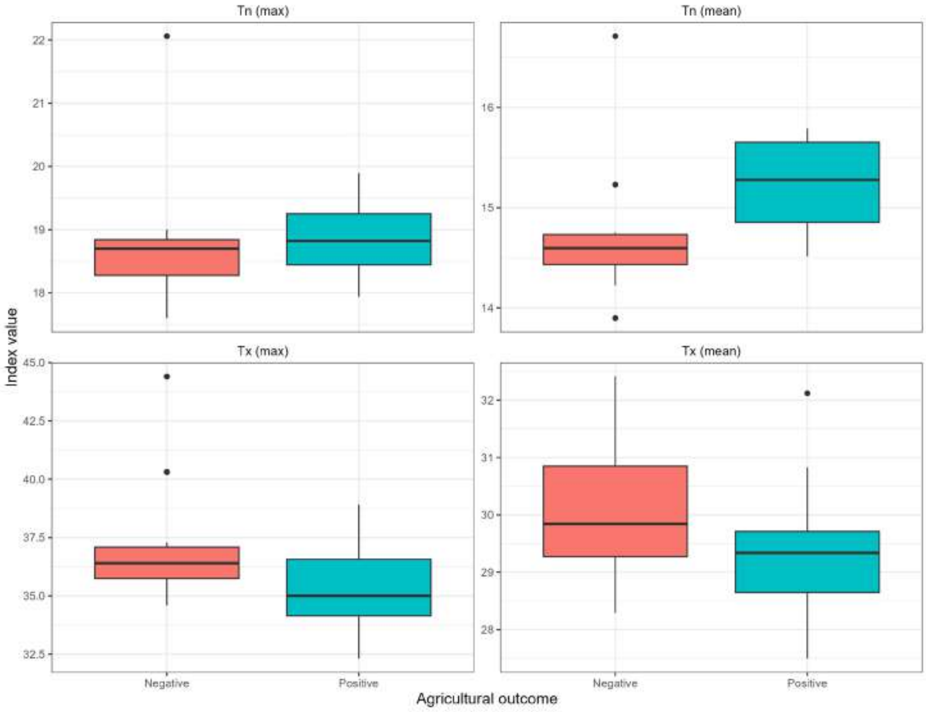

Figure 3.7: Boxplots of selected summer (December-February) temperature indices for maize for the Koppies district, grouped by years with positive and negative detrended, normalised maize yield.

Scatter plots of temperature indices versus detrended maize yield broadly reflect the patterns evident in the boxplots (Figure 3.8). Relationships involving Tx are the strongest, with both mean and maximum Tx exhibiting statistically significant negative correlations with maize yield ($\rho = -0.45$, $p = 0.027$ and $\rho = -0.43$, $p = 0.037$, respectively; Figure 3.8). Minimum temperature (Tn) shows a weaker response, with mean Tn characterised by a negative correlation that approaches statistical significance ($\rho = -0.40$, $p = 0.051$), while maximum Tn exhibits little to no association with yield (Figure 3.8). Together, these results suggest that elevated daytime temperatures, and to a lesser extent warmer nighttime conditions, were associated with reduced maize yields during the summer growing season. The consistency between the boxplot and scatter plot results reinforces the interpretation that temperature acts as a contributing stressor, with its influence likely amplified when combined with unfavourable moisture conditions.

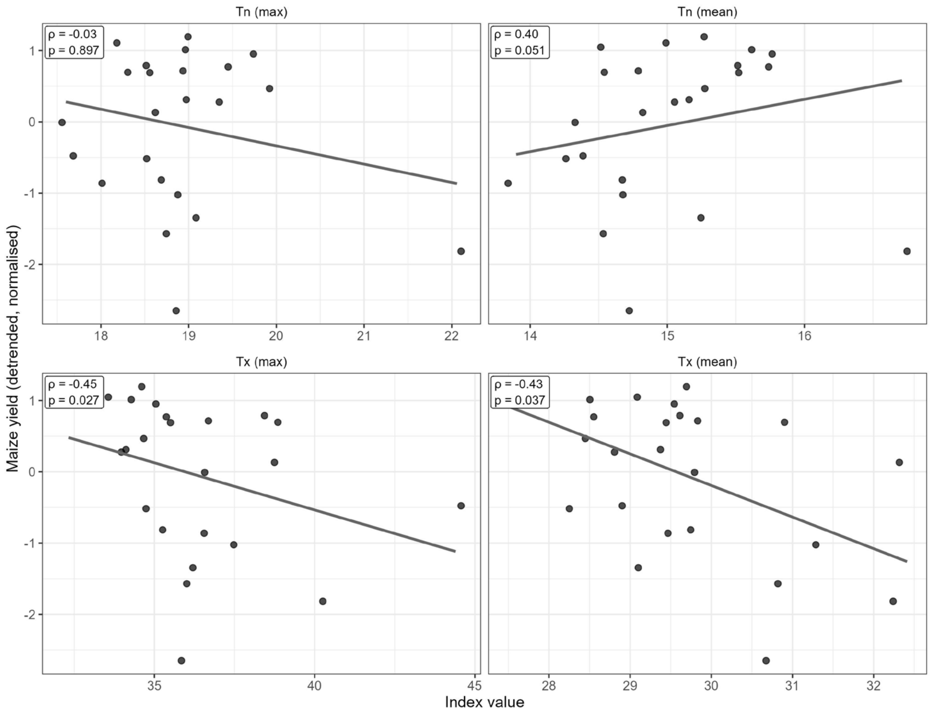

Figure 3.8: Scatter plots showing the relationship between selected summer (December-February) temperature indices (x-axis) and detrended, normalised maize yield for the Koppies district (y-axis). Each point represents a single summer season for a given year, pairing the climate index value with the corresponding detrended, normalised maize yield. Spearman's rank correlation coefficient (ρ) and associated p-value are shown for each index.

Taken together, the maize case study illustrates how climate indices related to rainfall, atmospheric water demand, and temperature can be used to contextualise interannual variability in crop yields. Rather than identifying precise thresholds or predictive relationships, the analysis demonstrates the value of summarising daily climate information into indices that reflect key agroclimatic stressors relevant to crop production. Within the Weather Risk app, these indices provide a practical means for grain farmers and advisors to assess seasonal climate conditions that may influence yield outcomes and inform management decisions.

3.2.3.3 Implications for the use of climate indices

Across both case studies, the results illustrate the added value of climate indices for interpreting agricultural outcomes beyond simple seasonal averages. By framing weather conditions in terms of agriculturally meaningful thresholds and accumulation periods, indices provide a practical bridge between climate data and on-farm impacts. While the analyses presented here are exploratory and not intended to identify definitive drivers, they demonstrate how indices available through the Weather Risk application can support situational awareness, retrospective assessment, and more proactive, risk-informed decision-making. For livestock systems, such information may assist farmers in anticipating periods of thermal or moisture stress and adjusting management practices accordingly, while for crop systems the indices can inform irrigation and heat-stress mitigation decisions. More broadly, these indices may also hold value for other actors in the agricultural value chain by supporting regional-scale assessments of production risk.

3.3 Case study two: evaluation of the AgERA5 and ERA5 datasets for calculating heavy rainfall indices

3.3.1 Introduction

South Africa benefits from a relatively dense and high-quality network of weather station observations, which provide invaluable records of rainfall variability and extremes (e.g., Moeletsi et al., 2022). However, while these observations are well-suited for point-based analyses, they are less able to fully characterise the spatial patterns of rainfall across the country, particularly for highly localised and episodic events such as heavy rainfall. In addition, station records may contain temporal gaps, which can complicate the consistent calculation of rainfall-derived indices over extended periods.

As a result, gridded datasets are commonly used to complement station observations, offering spatially continuous representations of rainfall that are well suited to regional-scale analyses (Mpungose et al., 2022; Thoithi et al., 2023). The reliability of such datasets, however, is highly dependent on their performance across different rainfall characteristics and temporal scales. Previous work by Steinkopf & Engelbrecht (2022) showed that the ERA5 reanalysis performs well over South Africa when evaluated using seasonal and annual rainfall totals. Whether this performance extends to rainfall-derived indices, particularly those describing extreme events, remains less well explored.

This case study presents selected results from an MSc study conducted by Ms Dimakatso Ndaleni, which, from 1980 to 2022, evaluates the suitability of ERA5-based datasets for analysing rainfall characteristics over South Africa using an index-based framework. Recognising that the reliability of gridded datasets is inherently location-specific, such that datasets perform well in some regions and are less reliable in other regions, the study assesses the ability of ERA5 and AgERA5 to represent heavy rainfall behaviour across different parts of the country. The primary aim was to determine whether these ERA5-based datasets can be reliably used to investigate rainfall characteristics, with specific emphasis in the current report on heavy and very heavy rainfall indices. Only some of the results relating to these indices are presented here, with the full analysis to be reported in the MSc dissertation and published following completion of the MSc degree.

3.3.2 Data and methodology

This case study evaluates the performance of ERA5-based gridded rainfall datasets for calculating rainfall indices over South Africa using an index-based comparison with weather station observations. While the above-mentioned analysis considered seven rainfall indices, only two threshold-based indices relevant to heavy rainfall are presented here. This includes the R10mm index, defined as the number of days with daily rainfall equal to or exceeding 10 mm (heavy rainfall days), and the R20mm index, defined as the number of days with daily rainfall equal to or exceeding 20 mm (very heavy rainfall days).

Daily rainfall observations were obtained for 1980-2022 from weather stations operated by the SAWS. To address temporal gaps in the station records, missing values were imputed using the National Oceanic and Atmospheric Administration Climate Prediction Center (NOAA CPC) rainfall dataset. Stations were selected based on their use in previous South Africa rainfall studies and were required to have less than 10% missing(e.g., Kruger & Nxumalo, 2017b; Roffe et al., 2021a; McBride et al., 2022)l., 2021a; McBride et al., 2022). In total, 44 weather stations were included, providing a generally well-distributed weather station spatial coverage across South Africa (Figure 3.9)

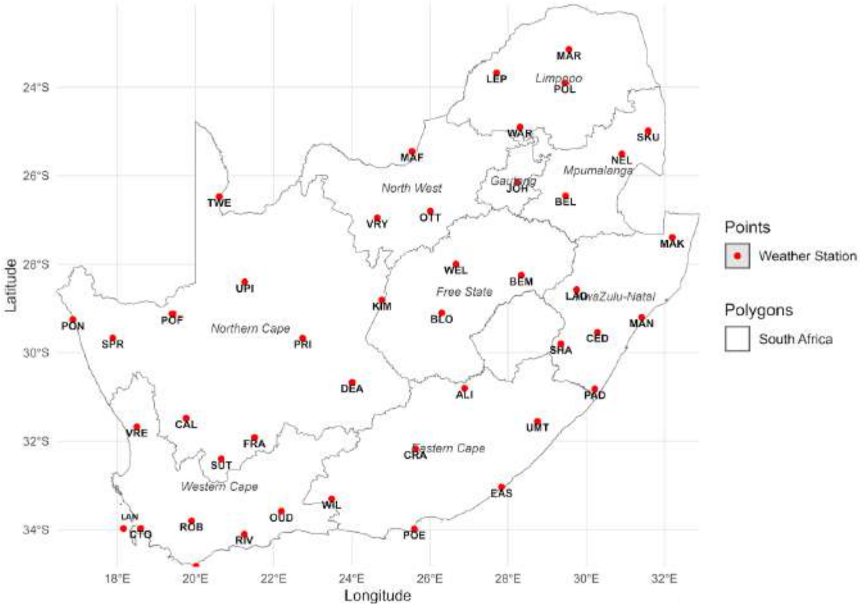

Figure 3.9: Locations of the weather stations used in this case study.

Gridded rainfall data were obtained from the European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis v5 (ERA5; with a grid resolution of 0.25°) and Agronomic ERA5 (AgERA5; with a grid resolution of 0.1°), collectively referred to here as ERA5-based datasets (Hersbach et al., 2020). Where necessary, the gridded rainfall datasets were pre-processed to sum hourly data to daily totals and convert units to mm for consistency with the weather station data. For direct comparison with station observations, gridded rainfall values were extracted at the geographic coordinates of each weather station, resulting in matched time series for each dataset and location. These matched time series were annual values of the R10mm and R20mm indices, computed, using the R statistical language, as the number of days with rainfall equating to 10-19.9 mm and ≥20 mm.

The evaluation of the ERA5-based datasets was undertaken using a combination of descriptive, statistical, and trend-based analyses, following Roffe and van der Walt (2023). Climatological mean values of the rainfall indices were first compared through visual inspection to assess overall consistency between station-based and gridded estimates. Quantitative comparisons included bias calculations and Mann-Whitney-Wilcoxon tests to assess differences in the data distributions, as well as Spearman rank correlations to evaluate temporal correspondence. Temporal trends in the indices were assessed using the Mann-Kendall trend test, with trend magnitude quantified using Sen's slope estimator. For the Mann-Whitney-Wilcoxon, Spearman, and Mann-Kendall tests, statistical significance was evaluated at the 5% significance ($\alpha = 0.05$) level.

3.3.3 Results and discussion

Figure 3.10 shows the annual mean number of heavy (R10mm) and very heavy (R20mm) rainfall days over South Africa for the period 1980-2022, derived from weather station observations and the ERA5 and AgERA5 datasets. Station-based results indicate a clear west-east gradient for both indices, with relatively few heavy rainfall days in the western interior and higher frequencies toward the eastern parts of the country (Figure 3.10). This broad spatial pattern is reproduced by both ERA5 and AgERA5 for R10mm and R20mm, with magnitudes generally consistent with station observations, ranging from approximately 0 to 50 days for R10mm and 0 to 15 days for R20mm (Figure 3.10). In addition to the large-scale gradient, both gridded datasets capture regions of locally higher rainfall frequency, including pockets along the southern coastal belt and the southwestern Cape Fold Mountain region, which are also evident in the station-based results (Figure 3.10). Overall, these results begin to support the suitability of ERA5 and AgERA5 for representing the spatial distribution of heavy and very heavy rainfall day frequencies over South Africa, while highlighting the need for further evaluation using additional statistical metrics and temporal analyses.

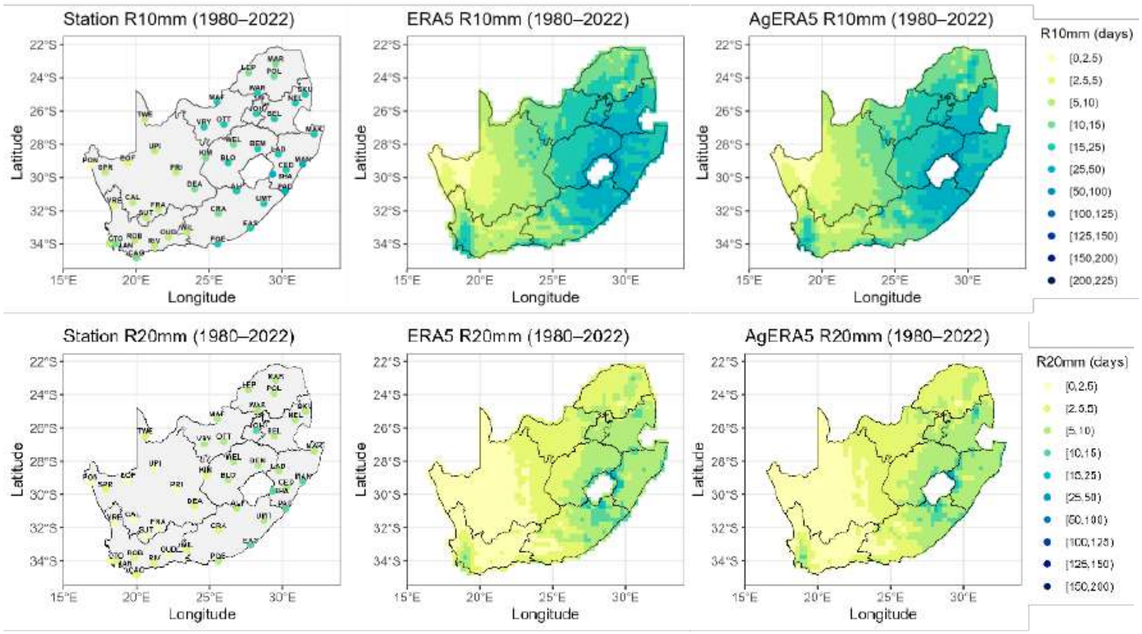

Figure 3.10: Mean annual number of heavy rainfall days (R10 mm; top) and very heavy rainfall days (R20 mm; bottom) over South Africa for the period 1980-2022, derived from weather station observations and the ERA5 and AgERA5 datasets.

Figure 3.11 presents the spatial distribution of Spearman rank correlation coefficients and biases for the number of heavy rainfall days (R10mm) at weather station locations across South Africa, comparing station observations with AgERA5 and ERA5 for the period 1980-2022. For AgERA5, 32 of the 44 stations were characterised by statistically significant correlations, while 31 stations exhibited significant correlations for ERA5, indicating that both datasets are generally able to reproduce the interannual variability of heavy rainfall day frequencies (Figure 3.11). Correlation coefficients are predominantly positive for both datasets, with most stations characterised by values of approximately 0.4 or higher, suggesting a moderate to strong correspondence with station-based variability (Figure 3.11). Only a small number of stations display negative correlations, notably at PON and DEA in the Northern Cape and at RIV in the Western Cape, for both ERA5 and AgERA5 (Figure 3.11). Despite this strong temporal correspondence, bias analysis reveals that both datasets tended to underestimate the number of heavy rainfall days, with consistently negative biases across all stations (Figure 3.11). While the magnitude of the bias is relatively small at most locations, typically less than approximately -1.6 days, many stations exhibit statistically significant biases (Figure 3.11). This indicates that, although ERA5 and AgERA5 capture year-to-year variability in R10mm well, their distributions differ from station observations at several locations, highlighting the need for caution when applying these datasets for threshold-based rainfall frequency analyses without further bias assessment or correction.

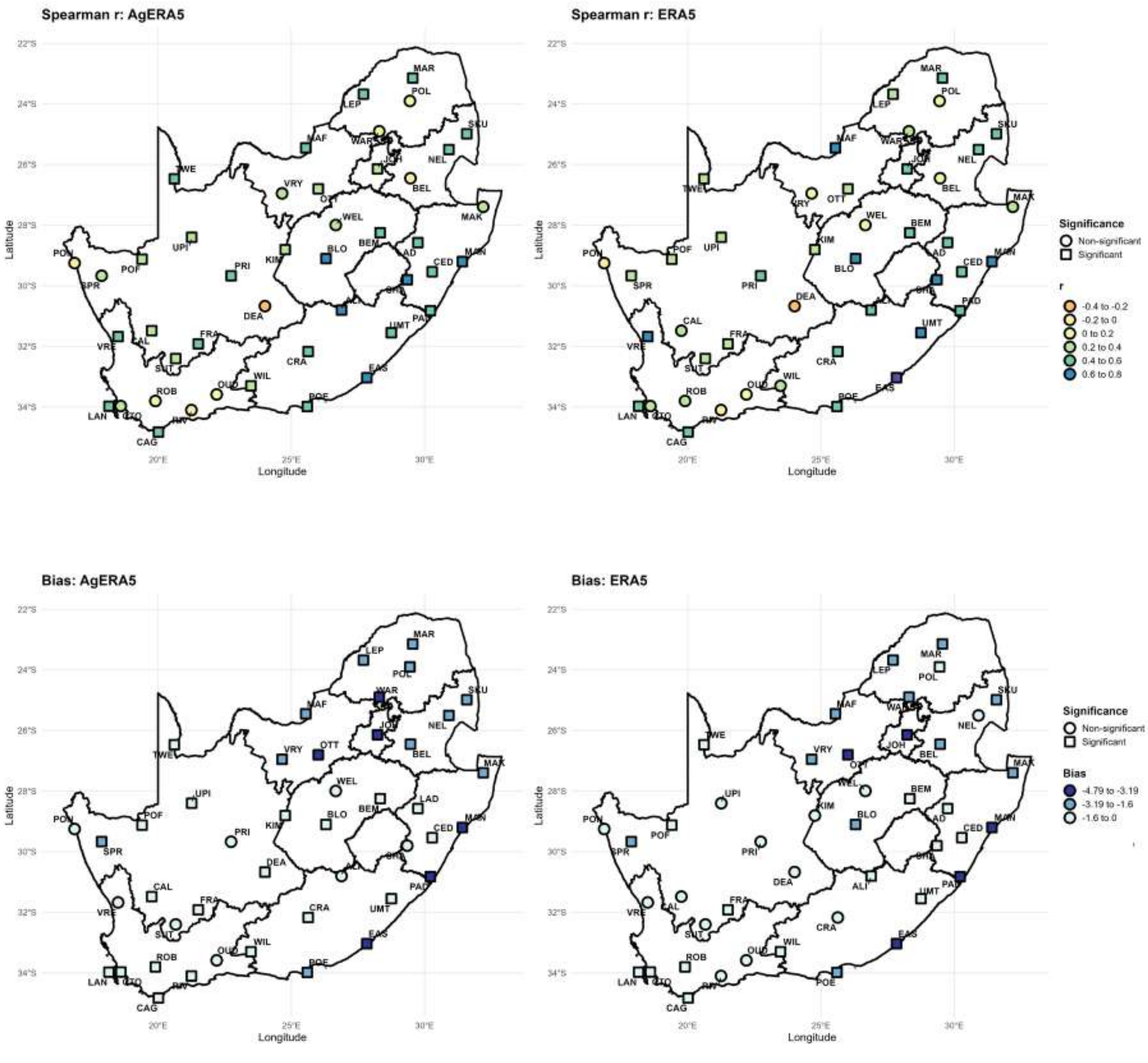

Figure 3.11: Spatial distribution of the Spearman rank correlation (top row) and bias (bottom row) for the number of heavy rainfall days (R10 mm) at weather station locations across South Africa, comparing station observations with AgERA5 and ERA5 datasets for the period 1980-2022. Statistically significant correlations and biases are indicated at the 5% significance level (α = 0.05). Correlation significance is assessed using the Spearman test, while bias significance is evaluated using the Mann-Whitney-Wilcoxon test.

Figure 3.12 shows the spatial distribution of Spearman rank correlation coefficients and biases for the number of very heavy rainfall days (R20mm) at weather station locations across South Africa, comparing station observations with AgERA5 and ERA5 for the period 1980-2022. Overall, the correlation patterns closely mirror those observed for the R10mm index (compare Figures 3.11 and 3.12). For AgERA5, 31 of the 44 stations exhibited statistically significant correlations, while 30 stations showed significant correlations for ERA5, indicating that both datasets generally capture the interannual variability of very heavy rainfall day frequencies (Figure 3.12). Correlation coefficients are predominantly positive, with most stations characterised by values of approximately 0.4 or higher, suggesting moderate to strong agreement with station-based variability (Figure 3.12). Negative correlations are limited to a small number of locations, specifically PON and DEA in the Northern Cape and RIV in the Western Cape, for both datasets (Figure 3.12). Despite this generally strong temporal correspondence, bias analysis reveals that both AgERA5 and ERA5 consistently underestimate the frequency of very heavy rainfall days, with negative biases observed at all stations (Figure 3.12). While the magnitude of these biases is relatively small at most locations, typically less than approximately -3.6 days, many stations exhibited statistically significant biases (Figure 3.12). This indicates that, similar to R10mm, the distributions of R20mm derived from the gridded datasets differ from those based on station observations, highlighting the need for caution when using ERA5 and AgERA5 to quantify the absolute frequency of very heavy rainfall days without additional bias assessment or adjustment.

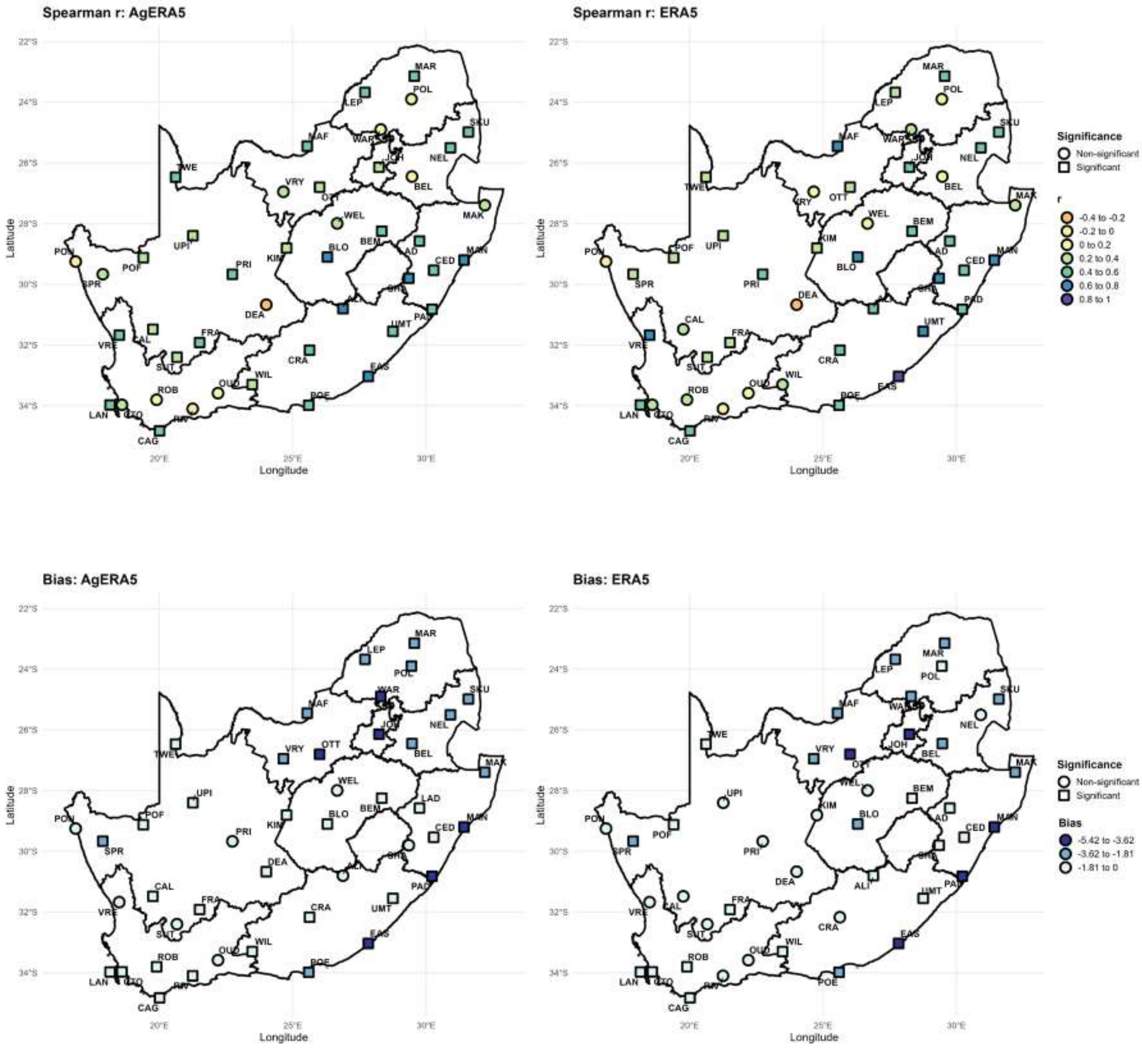

Figure 3.12: Spatial distribution of the Spearman rank correlation (top row) and bias (bottom row) for the number of very heavy rainfall days (R20 mm) at weather station locations across South Africa, comparing station observations with AgERA5 and ERA5 datasets for the period 1980-2022. Statistically significant correlations and biases are indicated at the 5% significance level (α = 0.05). Correlation significance is assessed using the Spearman test, while bias significance is evaluated using the Mann-Whitney-Wilcoxon test.

Figure 3.13 shows temporal trends in the number of heavy (R10mm) and very heavy (R20mm) rainfall days across South Africa for 1980-2022, derived from station observations and the AgERA5 and ERA5 datasets. Across both indices and all datasets, most stations exhibit statistically insignificant trends, indicating limited evidence of widespread, robust long-term changes in heavy rainfall-day frequencies over the analysis period (Figure 3.13). Although the magnitudes of Sen's slope were not always consistent between the station and gridded datasets, the direction of change is often similar at many locations, suggesting that the broad sign of trend is reasonably represented in most cases (Figure 3.13). However, there were several notable exceptions where station-based and gridded trends differed in direction and/or significance, highlighting important location-specific uncertainty. For R10mm, examples include POF

(Northern Cape), where station data indicated a negative trend while the gridded datasets indicated a positive trend; MAK (KwaZulu-Natal), where stations showed a statistically significant negative trend but the gridded datasets showed weak positive trends; and RIV (Western Cape), where stations indicated a significant positive trend while the gridded datasets showed weak negative trends (Figure 3.13). Similar behaviour is evident for R20mm, where most stations again showed insignificant trends, but isolated discrepancies occur, including Bethlehem, where station observations showed a significant positive trend but both gridded datasets indicated significant negative trends (Figure 3.13). These differences suggest that while the gridded datasets broadly capture the overall lack of strong, spatially coherent trend signals, trend interpretation at individual sites should be approached cautiously, as local-scale effects and dataset-specific biases can influence both trend direction and statistical significance.

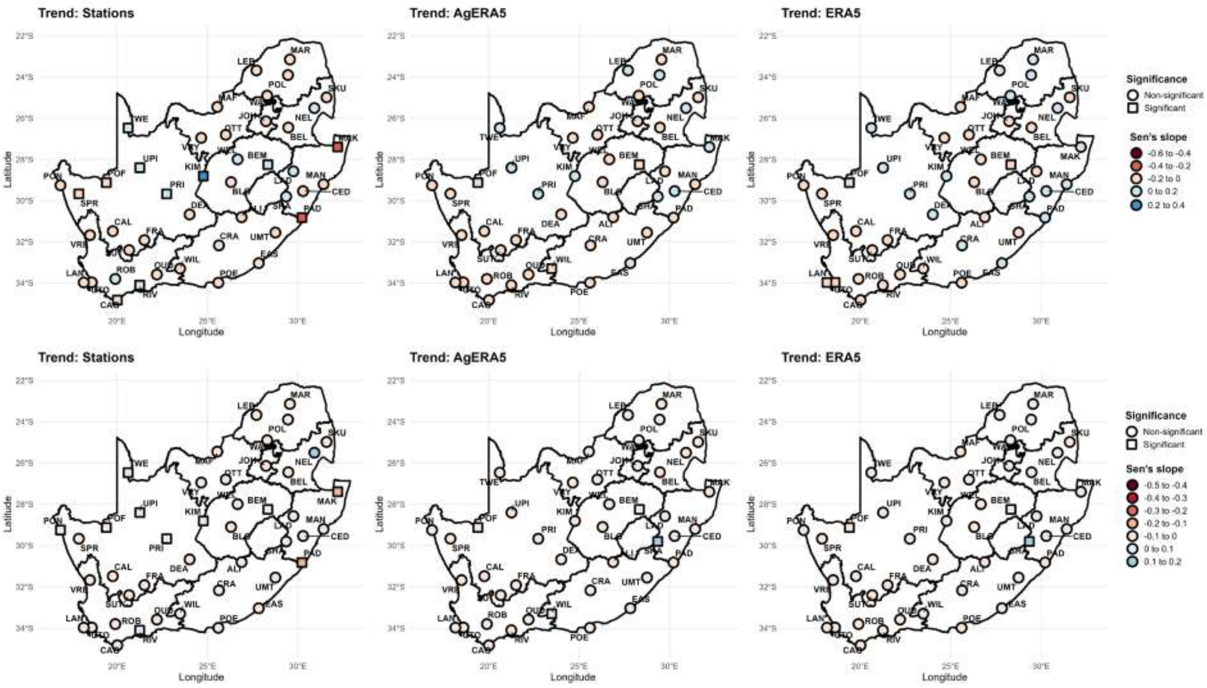

Figure 3.13: Spatial distribution of temporal trends in the number of heavy rainfall days (R10 mm; top row) and very heavy rainfall days (R20 mm; bottom row) across South Africa for the period 1980-2022, shown for weather station observations, AgERA5 and ERA5. Trend magnitude is represented by Sen's slope, while trend significance is assessed using the Mann-Kendall trend test. Statistically significant trends are indicated at the 5% significance level (α = 0.05).

Overall, the results presented in this case study begin to support the suitability of ERA5 and AgERA5 for analysing rainfall characteristics over South Africa, particularly for describing the large-scale spatial distribution of heavy and very heavy rainfall day frequencies and for capturing interannual variability patterns at many station locations. However, the consistent underestimation of rainfall-day frequencies (negative biases) and the station-level discrepancies evident in trend behaviour indicate that care is still required when using these datasets for threshold-based frequency indices at specific locations, especially where absolute magnitudes or local trend signals are of interest. It is also important to emphasise that only a small subset of the broader MSc analysis is presented here to illustrate key findings most relevant to this report; the full suite of indices, additional diagnostics, and extended interpretation are presented in the student’s MSc dissertation and are expected to be developed further in a peer-reviewed publication. Importantly, this case study provides a necessary foundation for identifying which ERA5-based datasets can be reliably used to compute heavy and very heavy rainfall frequency indices in subsequent applications and analyses.

3.4 Case study three: characteristics of precipitation over the Vaal Water Management Area

3.4.1 Introduction

Understanding the balance between precipitation and evapotranspiration (E-P) is fundamental to assessing freshwater availability and hydroclimatic variability (Majozi et al., 2017; Matimolane et al., 2025; Mengistu et al., 2025), particularly in regions of high population density and water demand. This case study draws on work conducted by Mr Munei Mugeri as part of his MSc research, which is investigating freshwater fluxes over the Vaal Water Management Area (WMA; Figure 3.14) for the period 1980-2023, with a focus on interannual variability and climatological patterns of moisture sources and transport pathways.

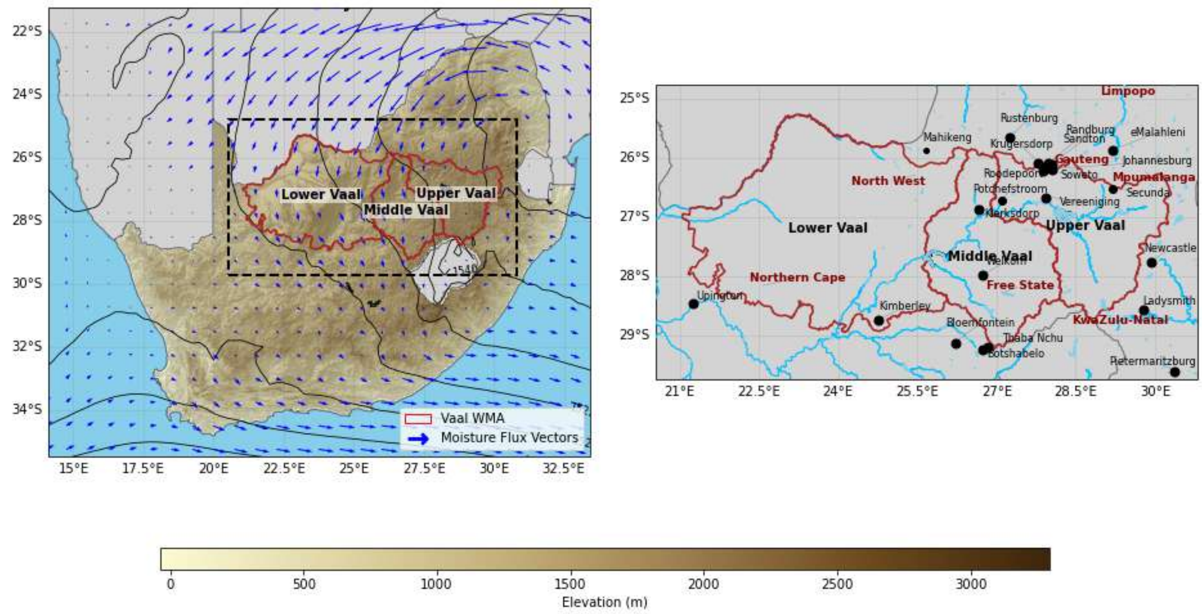

Figure 3.14: Map of the study region showing (left) the location of the Vaal Water Management Area (WMA) within South Africa, including regional elevation and extended summer season (October-April) moisture-flux vectors for 1980-2023, and (right) a zoomed-in view of the Vaal WMA highlighting major rivers and towns within and adjacent to the WMA.

The Vaal WMA was selected due to its socio-economic importance, supporting the largest proportion of South Africa’s population and underpinning major industrial, agricultural, and urban water demands (du Plessis, 2017, 2021). While the region has been extensively studied from a rainfall and water-resources perspective (e.g., Jury, 2016; Remilekun et al., 2020), comparatively little attention has been given to understanding the origins of moisture contributing to precipitation and how moisture transport pathways influence rainfall variability over time, with limited research of this nature in general over southern Africa (e.g., Rapolaki et al., 2019, 2020, 2021). Addressing this knowledge gap is critical for improving understanding of precipitation variability and potential future changes in freshwater availability.

This case study focuses specifically on the first objective of the MSc research, namely exploring the nature of precipitation (i.e., rainfall) over the Vaal WMA. Results presented here illustrate spatial and temporal patterns of rainfall using simple rainfall indices, including rainfall totals and anomalies, providing an applied example of how such indices can be used to characterise precipitation behaviour and to inform subsequent analyses of moisture sources and freshwater fluxes within the broader MSc study.

3.4.2 Data and methodology

This case study uses gridded precipitation (i.e., rainfall) data from the Climate Research Unit (CRU) and ERA5 reanalysis datasets for the period 1980-2023 to examine precipitation characteristics over the Vaal WMA. The CRU dataset, which is based on observed weather station records (Harris et al., 2020), was used as the reference dataset, while ERA5 precipitation was evaluated relative to CRU. The CRU dataset has a spatial resolution of 0.5° (Harris et al., 2020), whereas ERA5 provides precipitation data at a finer spatial resolution of 0.25° (Hersbach et al., 2020). Both datasets were pre-processed where necessary to ensure consistency in units, with precipitation expressed in mm.

CRU precipitation was used to assess the suitability of ERA5 for representing precipitation amounts over the Vaal WMA. Area-averaged precipitation totals were calculated for each dataset and compared across multiple temporal scales, including annual totals, extended summer (October-April), early summer (October-December), and late summer (January-April). This comparison provides a quality check on ERA5 precipitation performance prior to its application in subsequent freshwater flux and moisture source analyses within the broader MSc study.

Given the strong seasonality of rainfall in the region, analyses focused primarily on summer precipitation as the Vaal WMA forms part of the summer rainfall zone of South Africa (Roffe et al., 2021a). The response of precipitation to El Niño-Southern Oscillation (ENSO) phases was examined for extended, early, and late summer periods by calculating standardised rainfall anomalies (SRAs) and analysing area-averaged precipitation behaviour during seasons with La Niña, neutral, and El Niño conditions (Rapolaki et al., 2021). Spatial variability in precipitation was further explored using annual precipitation composites, constructed by grouping years into dry (<33rd percentile), normal (33rd-67th percentile), and wet (>67th percentile) terciles (Tippett et al., 2007).

Temporal trends in precipitation were assessed for annual, extended summer, early summer, and late summer periods using the non-parametric Mann-Kendall trend test, with trend magnitude quantified using Sen's slope estimator, and statistical significance was evaluated at the 5% significance level ($\alpha = 0.05$; Mahlalela et al., 2020).

3.4.3 Results and discussion

Figure 3.15 shows the mean annual total precipitation over the Vaal WMA derived from ERA5 and the CRU reference dataset for the period 1980-2023. Overall, the two datasets show strong agreement in terms of interannual variability, with wet and dry years generally coinciding, providing confidence in the ability of ERA5 to represent year-to-year precipitation fluctuations over the region (Figure 3.15). Being the main dataset for this study, notably ERA5-derived annual rainfall totals ranged from approximately 400 mm.year^{-1} during drier years (e.g., 1992 and 2015) to close to 900 mm.year^{-1} during wetter years (e.g., 1988, 2000, and 2006), broadly consistent with CRU estimates (Figure 3.15). However, ERA5 exhibits a systematic wet bias relative to CRU, with annual totals typically exceeding those from the reference dataset (Figure 3.15). This bias is evident throughout the study period, especially for years such as 2022, where ERA5 estimates were approximately 200 mm higher than CRU (Figure 3.15). Despite this positive bias in absolute magnitude, the close correspondence in temporal behaviour supports the use of ERA5 as the primary dataset for analysing precipitation variability and patterns over the Vaal WMA in the remainder of the study, while highlighting the need for caution when interpreting absolute rainfall amounts.

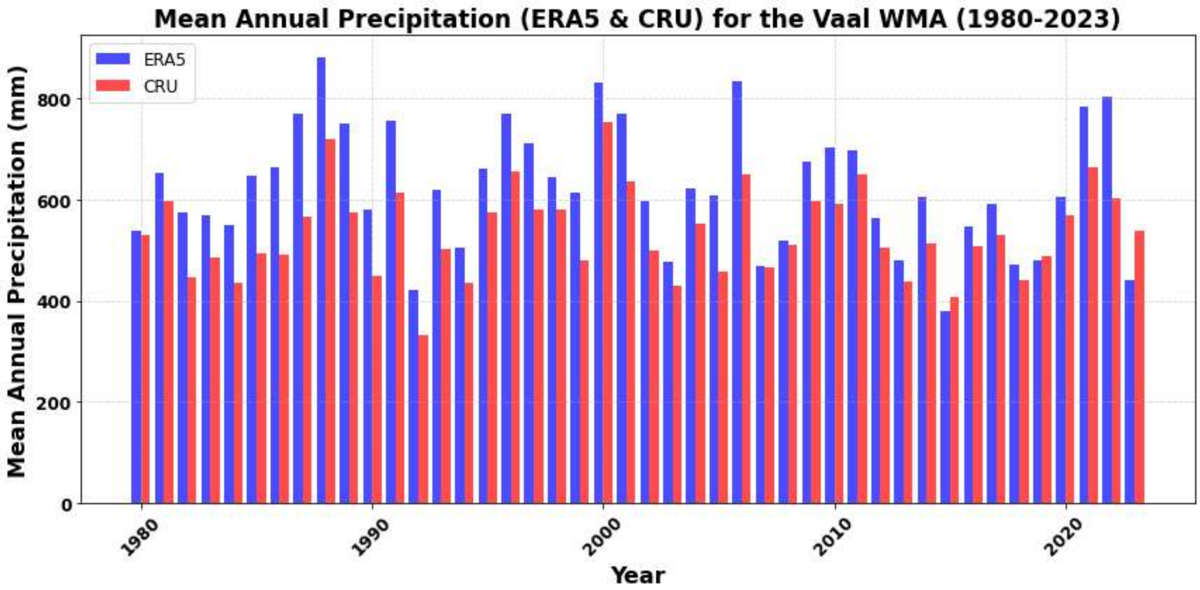

Figure 3.15: Mean annual total precipitation time series for the Vaal Water Management Area (WMA) derived from ERA5 (blue), and CRU (red) for the period 1980-2023.

Figure 3.16 shows the time series of mean seasonal precipitation over the VMA derived from ERA5 and the CRU reference dataset for the extended summer (October-April), early summer (October-December), and late summer (January-April) periods during 1980-2023. Across all three seasonal aggregations, ERA5 and CRU displayed strong agreement in interannual variability, with wet and dry seasons generally coinciding, indicating that ERA5 captured the timing and relative magnitude of seasonal precipitation variability well (Figure 3.16). However, a consistent wet bias in ERA5 is evident across all periods, confirming that this bias is systematic rather than season-specific (Figure 3.16). The largest seasonal differences occur during particularly wet years, such as 2000 for the extended summer season, where ERA5 exceeded CRU by approximately 150 mm, while notable biases of up to roughly 100 mm are evident for early summer in 2023 and late summer in 2006 (Figure 3.16). In terms of magnitude, ERA5-derived precipitation totals ranged from approximately 200 to 800 mm.year^{-1} for the extended summer period, from around 100 to 350 mm.year^{-1} for early summer, and from roughly 150 to 500 mm.year^{-1} for late summer, all of which were values broadly consistent with CRU despite the positive bias (Figure 3.16). Overall, these results reinforce the suitability of ERA5 for analysing seasonal precipitation variability over the Vaal WMA, while emphasising that absolute rainfall totals, particularly during wetter seasons, should be interpreted with caution.

Figure 3.17 illustrates SRAs for the extended summer (October-April), early summer (October-December), and late summer (January-April) seasons, grouped by ENSO phase, and highlights a clear modulation of rainfall variability over the Vaal WMA by large-scale climate drivers. For the extended summer period, particularly wet years included 1988, 2000, 2001, 2006, 2021, and 2022, of which three (i.e., 2000, 2021, and 2022) coincided with La Niña conditions, while two occurred during neutral phases (Figure 3.17). Overall, La Niña October-April seasons were predominantly associated with positive anomalies, with 7 out of 11 La Niña years exhibiting wetter-than-average conditions (Figure 3.17). In contrast, notably dry extended summers occurred in 1992, 2003, and 2015, all of which coincided with El Niño conditions (Figure 3.17). Across all El Niño October-April seasons, 6 out of 10 were characterised by negative SRAs (Figure 3.17).

A similar but seasonally nuanced ENSO signal was evident for early summer (October-December). Particularly wet October-December seasons included 1993, 1995, and 2001, with 1995 coinciding with La Niña conditions, and overall, 11 out of 17 La Niña October-December seasons exhibited positive anomalies (Figure 3.17). Conversely, strongly dry early summers occurred in 2015 and 2018, with both associated with El Niño conditions, while 9 out of 14 El Niño October-December seasons were characterised by negative SRAs (Figure 3.17). For late summer (January-April), wet conditions were most evident in 1988, 2000, 2006, and 2022, of which all except 1988 occurred during La Niña phases (Figure 3.17). Overall, 8 out of 13 La Niña January-April seasons exhibited positive SRA anomalies (Figure 3.17). Particularly dry late summers were less frequent but included 1992 and 2007, with 1992 occurring during El Niño conditions, and 9 out of 11 El Niño January-April seasons were characterised by negative SRAs (Figure 3.17). Collectively, these results demonstrate a coherent ENSO influence on seasonal rainfall variability over the Vaal WMA, with La Niña phases generally favouring wetter-than-normal conditions and El Niño phases were associated with an increased likelihood of drier-than-normal seasons, particularly during the extended and late summer periods (Figure 3.17).

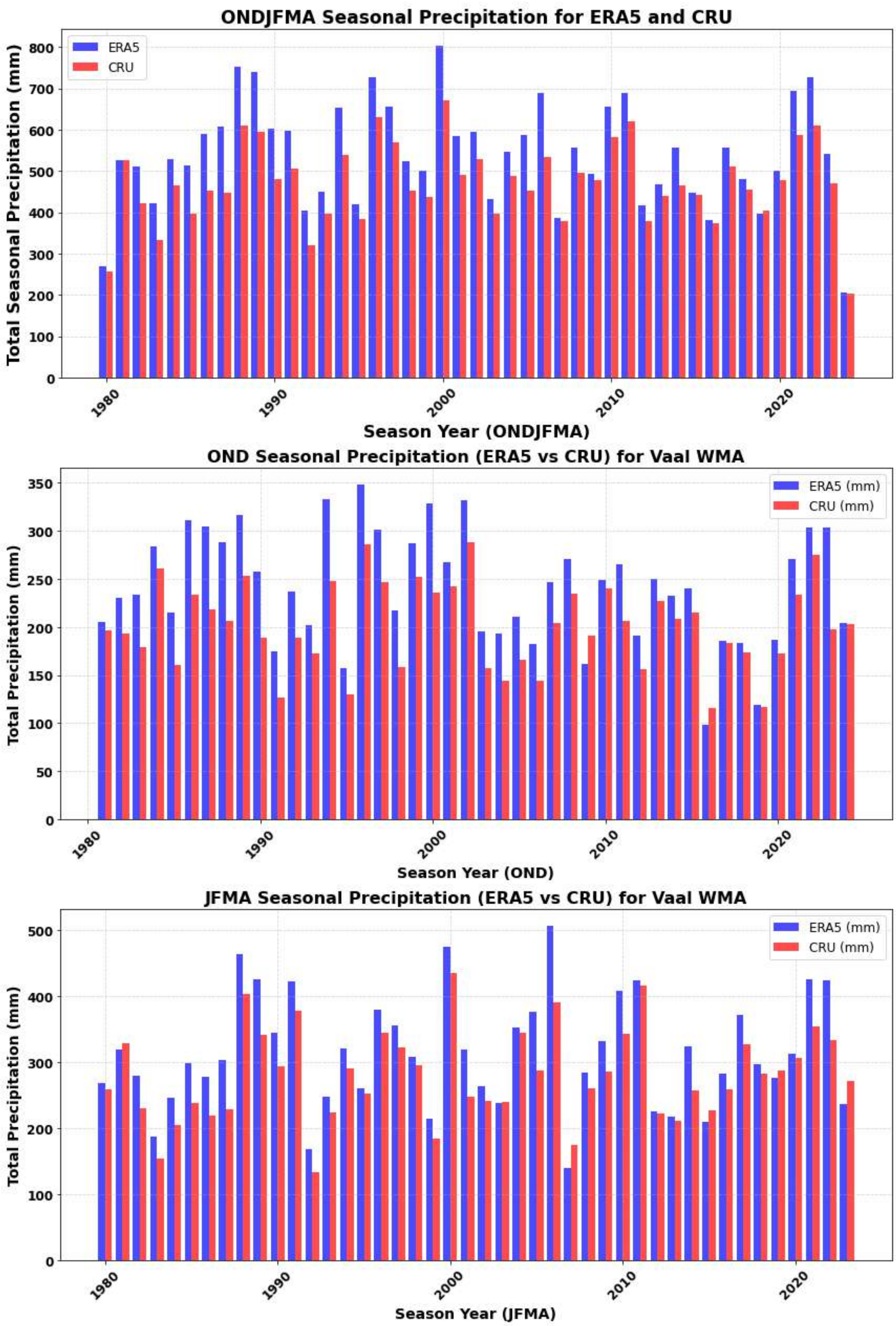

Figure 3.16: Time series of mean total precipitation for the Vaal Water Management Area (WMA) derived from ERA5 (blue) and CRU (red) for the period 1980-2023, shown for (top row) the extended summer season (October-April), (middle row) early summer (October-December), and (bottom row) late summer (January-April).

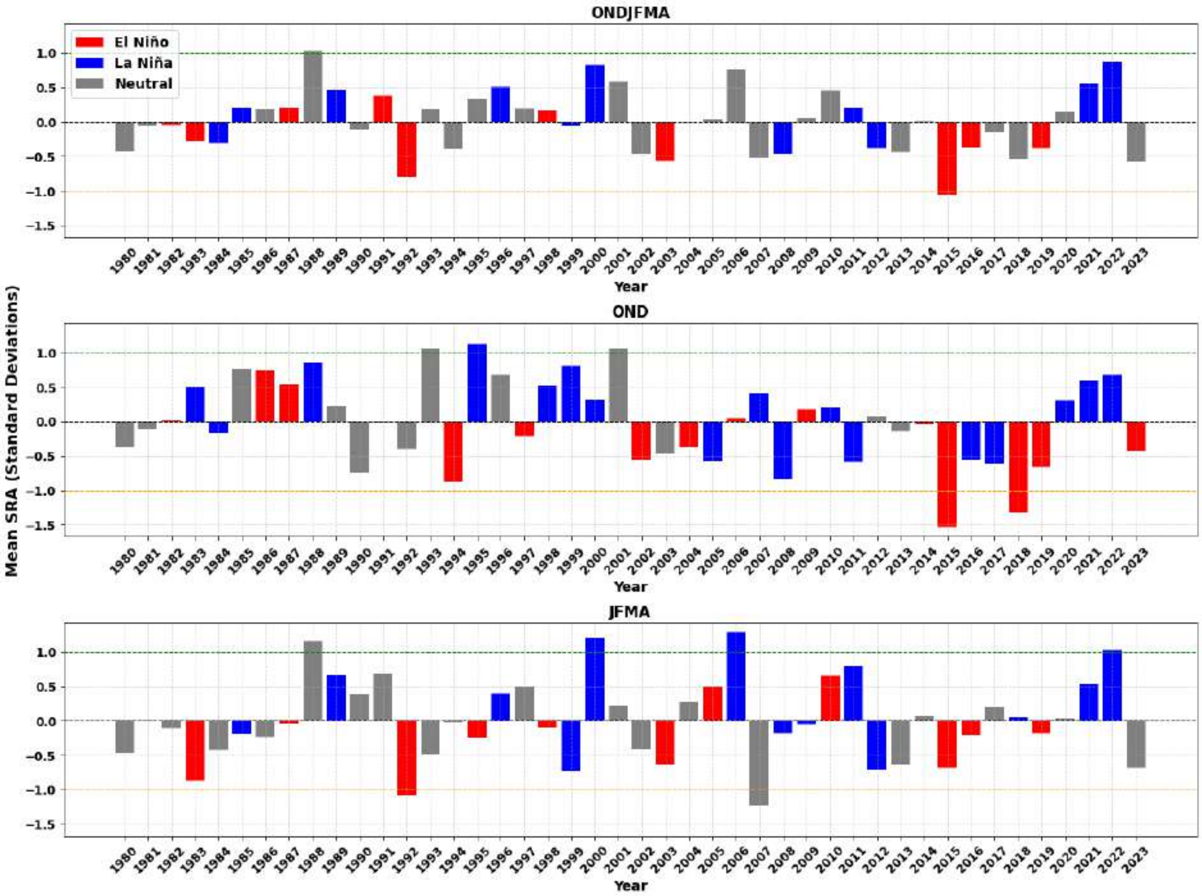

Figure 3.17: Standardised Rainfall Anomalies (SRAs) by El Niño-Southern Oscillation (ENSO) phase for the extended summer season (October-April), early summer (October-December), and late summer (January-April), derived from ERA5 total precipitation data. Bars show mean SRA values for El Niño (red), La Niña (blue), and Neutral (grey) conditions, where anomalies are calculated relative to the long-term average for the corresponding months over 1980-2023. Horizontal green and orange reference lines, respectively, at +1 and −1 denote significantly wetter and drier than normal conditions, respectively.

Figure 3.18 shows the spatial distribution of composite annual precipitation across the Vaal WMA for dry, normal, and wet years over the period 1980-2023. Across all three composites, a pronounced west-east rainfall gradient is evident, consistent with the broader climatological pattern over South Africa, with wetter conditions occurring toward the eastern parts of the basin (Figure 3.18). During wet years, the Upper and Middle Vaal sub-basins experienced the highest precipitation amounts, typically ranging from approximately 2 to 4 mm.day^{-1}, while the Lower Vaal remained comparatively drier, with values generally between 1 and 2 mm.day^{-1} (Figure 3.18). In normal years, precipitation across the Lower and much of the Middle Vaal was similarly characterised by values of around 1 to 2 mm.day^{-1}, while the Upper Vaal showed moderately higher rainfall of approximately 2 to 3 mm.day^{-1} (Figure 3.18). During dry years, precipitation was suppressed across the basin, with the Lower Vaal receiving up to around 1 mm.day^{-1}, the Middle Vaal generally between 1 and 2 mm.day^{-1}, while the Upper Vaal maintained slightly higher values of approximately 1 to 3 mm.day^{-1} (Figure 3.18). These composites demonstrate that, despite substantial interannual variability in total rainfall, the spatial organisation of precipitation across the Vaal WMA remains coherent, with the eastern and upstream regions consistently wetter than the western and downstream areas under both dry and wet conditions.

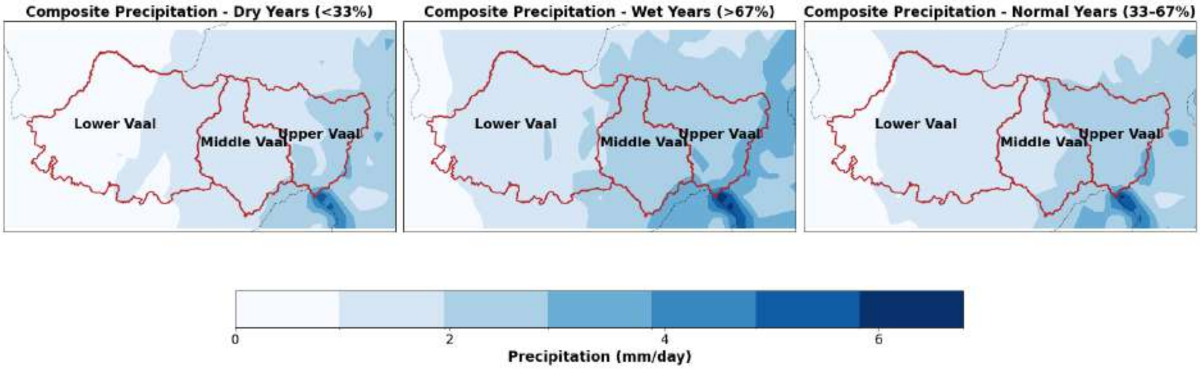

Figure 3.18: Spatial distribution of composite annual precipitation for 1980-2023 across the Vaal Water Management Area (WMA), categorised as (a) dry years (<33rd percentile), (b) wet years (>67th percentile), and (c) normal years (33rd-67th percentile), derived from ERA5 total precipitation data. All panels are overlaid with the Vaal WMA boundary (dark red), delineating the Upper, Middle, and Lower Vaal sub-basins.

Figure 3.19 illustrates the spatial distribution of precipitation trends across the Vaal WMA for the period 1980-2023, based on ERA5 total precipitation. At the annual scale, rainfall was predominantly characterised by declining trends across much of the basin, with the strongest drying signals evident over the Upper Vaal and adjacent Middle Vaal regions (Figure 3.19). In these areas, Sen's slope values reached approximately -4.5 mm.year^{-1}, and several grid cells exhibited statistically significant negative trends, particularly along the transition zone between the Upper and Middle Vaal sub-basins (Figure 3.19). A similar spatial pattern was observed for the extended summer season (October-April), which was also dominated by declining precipitation trends, although no statistically significant trends were detected for this period (Figure 3.19). The magnitude of drying during the extended summer reached up to around -4 mm.year^{-1} in the Upper and Middle Vaal regions, indicating that reductions during this season were the primary contributor to the observed annual drying signal (Figure 3.19). Early summer (October-December) trends showed widespread declines across all three sub-basins, with Sen's slope values reaching approximately -3 mm.year^{-1}, and numerous statistically significant trends were distributed across the basin (Figure 3.19). This suggests a robust reduction in early-season rainfall was evident during 1980 to 2023, which has important implications for seasonal rainfall accumulation and the timing of effective moisture availability. In contrast, late summer (January-April) trends indicated a partial reorganisation of seasonal rainfall, with weak positive trends evident across much of the basin, reaching up to approximately 2 mm.year^{-1} (Figure 3.19). Although none of these late summer trends were statistically significant, their spatial coherence suggests a tendency toward increased rainfall later in the season, consistent with a potential shift toward delayed seasonal rainfall onset rather than a uniform reduction in summer precipitation.

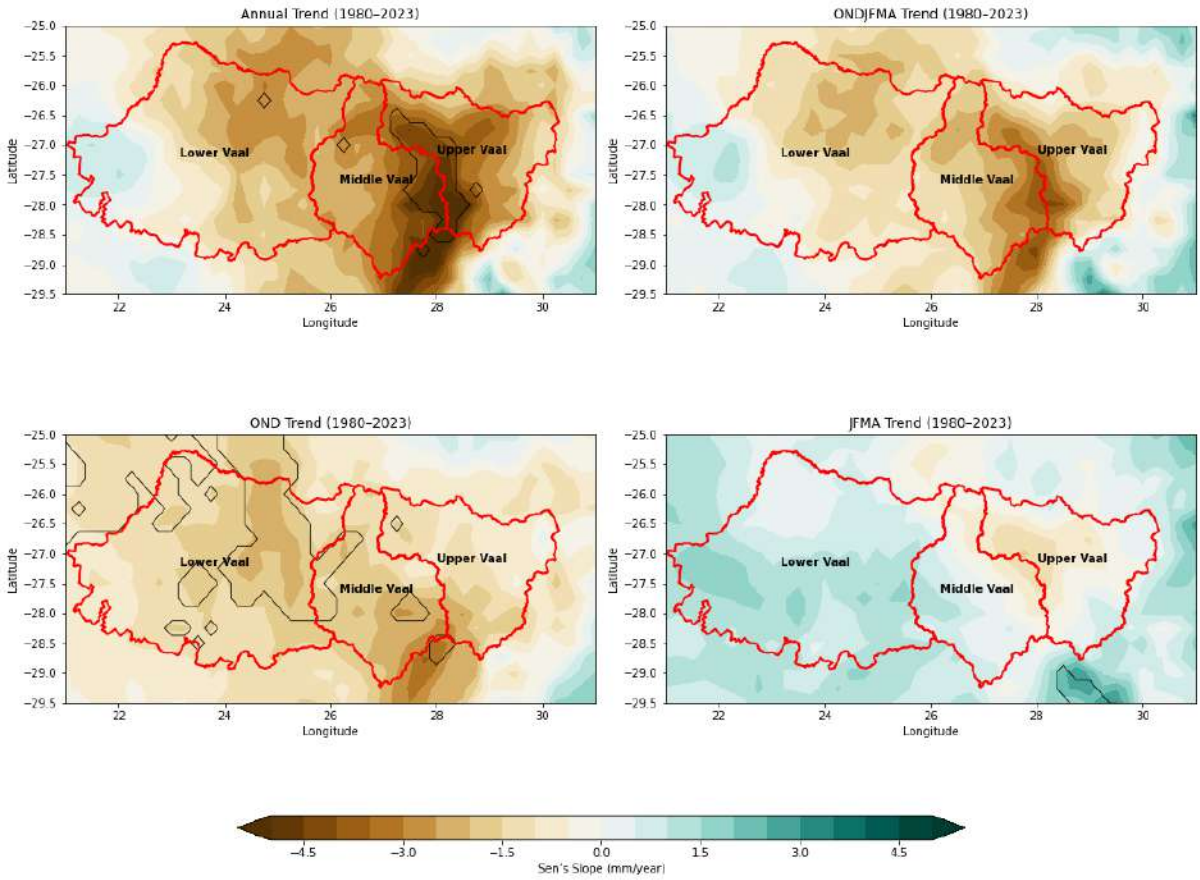

Figure 3.19: Spatial distribution of Sen's slope (mm.year^{-1}) of annual precipitation across the Vaal Water Management Area (WMA), derived from ERA5 total precipitation data for the period 1980-2023. Black contours denote statistically significant trends ($p < 0.05$), as assessed using the Mann-Kendall trend test. Red boundaries delineate the Upper, Middle, and Lower Vaal WMAs.

Overall, this case study demonstrates that ERA5 provides a robust and internally consistent basis for characterising precipitation variability and change over the Vaal WMA, with good agreement relative to the CRU reference dataset in terms of interannual variability and seasonal behaviour, despite the presence of a systematic wet bias in absolute rainfall amounts. The results show that rainfall variability across the basin was strongly seasonal and spatially structured, with wetter conditions consistently concentrated in the eastern and upper parts of the catchment, and clear modulation by ENSO phase occurred, particularly during the extended and early summer periods. Composite analyses further highlighted coherent spatial contrasts between dry, normal, and wet years, reinforcing the dominance of large-scale circulation controls on precipitation distribution across the basin. Trend analyses indicate that the observed long-term drying signal was primarily driven by declines in early summer and extended summer rainfall, while late summer rainfall showed weak, spatially coherent increases, suggesting a potential reorganisation of seasonal rainfall timing rather than a uniform decrease in summer precipitation. Collectively, these findings provide important context for subsequent analyses of freshwater fluxes and moisture source contributions over the Vaal system and demonstrate the value of rainfall indices and seasonal diagnostics for understanding hydrological sensitivity in South Africa's most socio-economically critical water management area.

3.5 Case study four: evaluation of ERA5-based datasets for calculating cold temperature indices

3.5.1 Introduction

Observed and projected warming over southern Africa has been widely documented, with robust increases in average surface air temperatures and extremely high temperature events reported since the mid-twentieth century (van der Walt & Fitchett, 2021; Meque et al., 2022). In contrast, the frequency and magnitude of ELTEs have generally declined (van der Walt & Fitchett, 2020b; Meque et al., 2024). Despite these trends, ELTEs continue to occur across the region, particularly during the austral winter (June-August) season, and can have substantial socio-economic and agricultural impacts, including frost damage to crops (Moeletsi & Tongwane, 2017b), livestock losses (Archer et al., 2021), increased energy demand (Mudzingiri et al., 2024), and cold stress in vulnerable communities (Roffe et al., 2023). These impacts highlight the continued need to monitor and characterise cold temperature extremes, even under a warming climate.

The analysis and monitoring of ELTEs traditionally rely on weather station observations; however, due to various geographic characteristics (e.g., complex topography and surrounding oceans), station data alone cannot fully capture the spatial variability of temperature extremes across southern Africa (Roffe & van der Walt, 2023). Consequently, gridded temperature datasets, including reanalysis products, are frequently used to complement station-based analyses(e.g., Serykh et al., 2025). The performance of such datasets is known to vary spatially and temporally, underscoring the importance of evaluating their suitability before application, particularly for extreme temperature indices (Roffe & van der Walt, 2023).

Therefore, drawing on work presented in the proceedings of the 2024 Biennial Conference of the Society of South African Geographers (Roffe & Singo, 2024; see Appendix 2.2), this case study evaluates the performance of ERA5-based temperature datasets, namely ERA5, ECMWF ERA5 reanalysis for the land component (i.e., ERA5-Land), and AgERA5, for representing cold temperature characteristics over South Africa. While the original analysis considered eight temperature indices, only two indices are presented here, including TXn, defined as the coldest daytime maximum temperature, and TNn, defined as the coldest nighttime minimum temperature. The focus is on assessing the ability of these datasets to represent winter (June-August) ELTEs, providing insight into their suitability for studying ELTEs over South Africa.

3.5.2 Data and methodology

This case study evaluates the performance of ERA5-based temperature datasets for representing ELTE characteristics over South Africa. The analysis uses the NOAA CPC observation-based gridded temperature dataset as the reference, following the approach of Roffe and van der Walt (2023). The NOAA CPC dataset was selected due to its relatively fine spatial resolution, availability of daily minimum and maximum temperature variables, and demonstrated reliability over southern Africa. ERA5, ERA5-Land, and AgERA5 were selected for evaluation as they provide the required temperature variables, have suitable spatial and temporal resolution for climate monitoring, and are updated regularly, making them relevant for operational applications. Dataset pre-processing and index calculations followed the methods described in Roffe and van der Walt (2023), using Climate Data Operators and R software.

While the original analysis considered eight cold temperature indices, only two indices are presented here. This includes TXn, defined as the coldest daytime maximum temperature, and

TNn, defined as the coldest nighttime minimum temperature. Indices were calculated for the austral winter season (June-August) over the period 1979-2021, corresponding to the season during which ELTEs are most likely to occur over southern Africa (van der Walt & Fitchett, 2020b).

Dataset performance was evaluated using a combination of spatial and temporal analyses, following Roffe and van der Walt (2023). Spatial comparisons included climatological mapping of the indices, bias calculations relative to the NOAA CPC reference dataset, and non-parametric statistical testing using the Mann-Whitney-Wilcoxon test. Temporal correspondence was assessed using Spearman's rank correlation, while trends were evaluated using the Mann-Kendall trend test with Sen's slope estimator. For regional-scale assessment, nominally homogeneous winter thermal regions were defined using k-means clustering based on June-August Tn climatology (Figure 3.24), and time series of regionally averaged indices were analysed. Statistical significance for all tests was assessed at the 5% significance ($\alpha = 0.05$) level.

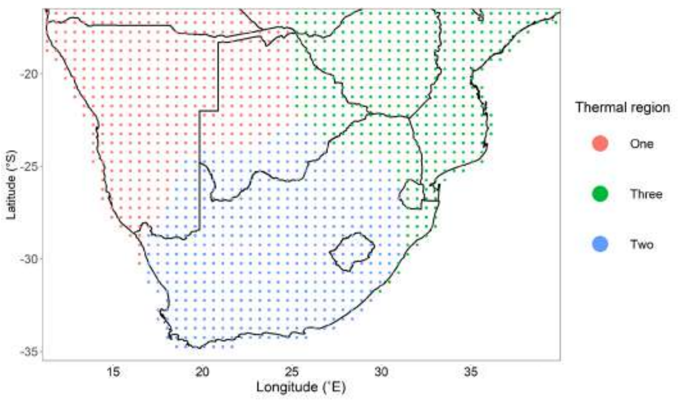

Figure 3.20: Thermal regions defined for the data evaluation.

3.5.3 Results and discussion

Figure 3.21 shows the winter (June-August) climatology of the coldest day (TXn) and coldest night (TNn) temperatures for the period 1979-2021, derived from the NOAA CPC reference dataset and the ERA5-based reanalysis products. Despite differences in spatial resolution, the ERA5-based datasets reproduced spatial patterns that are broadly consistent with the reference dataset for both indices, with comparable large-scale gradients and similar magnitude ranges across much of the domain (Figure 3.21). For TXn, lower temperatures (approximately -2 to 6 °C) were consistently evident over higher elevation regions, while substantially higher values, reaching up to roughly 30 °C, occurred at lower elevations across all datasets (Figure 3.21). A similarly coherent elevation-dependent pattern is evident for TNn, with lower coldest-night temperatures over elevated regions and higher values over lower-lying areas (Figure 3.21). However, compared to the NOAA CPC dataset, the ERA5-based products show systematically warmer TNn values in cooler regions, with the lowest TNn values extending farther north in the reference dataset (Figure 3.21). This indicates a warm bias in the ERA5-based datasets for the coldest night temperatures, particularly in regions characterised by persistently low winter minimum temperatures. Overall, these results indicate that the ERA5-based datasets capture the broad spatial structure of winter cold temperature characteristics, while highlighting systematic differences in the representation of extreme low nighttime temperatures.

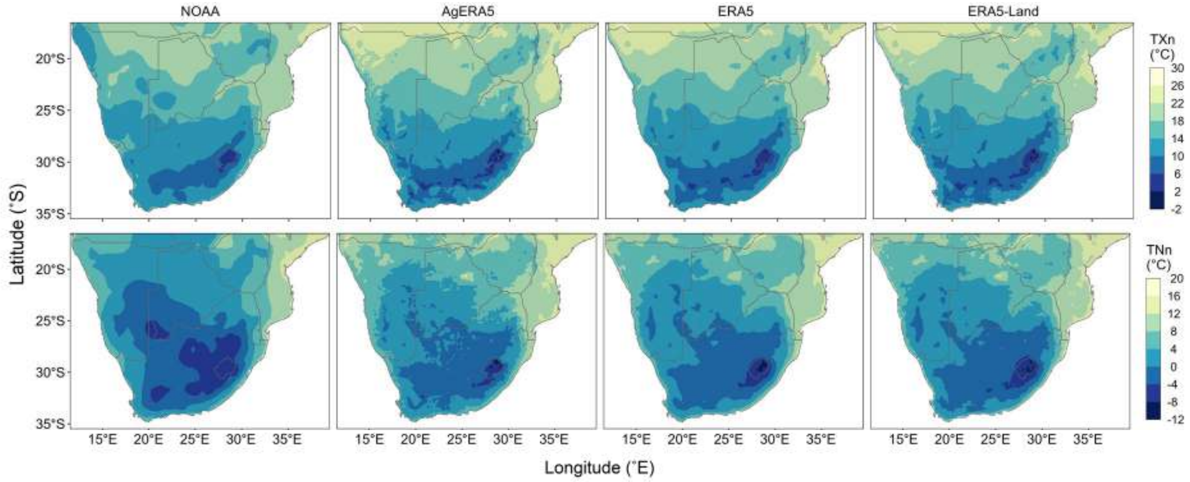

Figure 3.21: Maps showing the winter (June-August) climatology of the coldest day (TXn) and coldest night (TNn) for the period 1979-2021, derived from the NOAA CPC reference dataset and ERA5-based reanalysis products, including AgERA5, ERA5, and ERA5-Land. All variables are mapped at the nominal spatial resolution of each dataset.

Figure 3.22 presents bias maps for the winter (June-August) cold temperature indices TXn and TNn, comparing the ERA5-based reanalysis products with the NOAA CPC reference dataset for the period 1979-2021. Although the ERA5-based datasets reproduced broadly consistent climatological patterns for both indices, substantial biases are evident across much of the study region (Figure 3.22). The spatial distribution of biases is similar across AgERA5, ERA5, and ERA5-Land, as is the pattern of statistically significant and insignificant grid cells, indicating coherent regions where the reanalysis products differ systematically from the reference dataset (Figure 3.22). For both TXn and TNn, a large proportion of the domain was characterised by statistically significant biases, with magnitudes generally ranging between approximately -8 and 8 °C (Figure 3.22). For TXn, biases show a mixed pattern, with predominantly cool biases over much of the interior and warmer biases of up to roughly 4 °C over central northern and eastern regions (Figure 3.22). In contrast, TNn exhibited a more spatially extensive warm bias, affecting nearly the entire study region, with the largest positive biases, reaching approximately 12 °C, over central and northern areas (Figure 3.22). These results indicate that while ERA5-based datasets capture the broad spatial structure of cold temperature extreme magnitudes, they tend to overestimate the coldest night temperatures and, to a lesser extent, misrepresent coldest day temperatures, highlighting important limitations in their representation of extreme low temperature magnitudes.

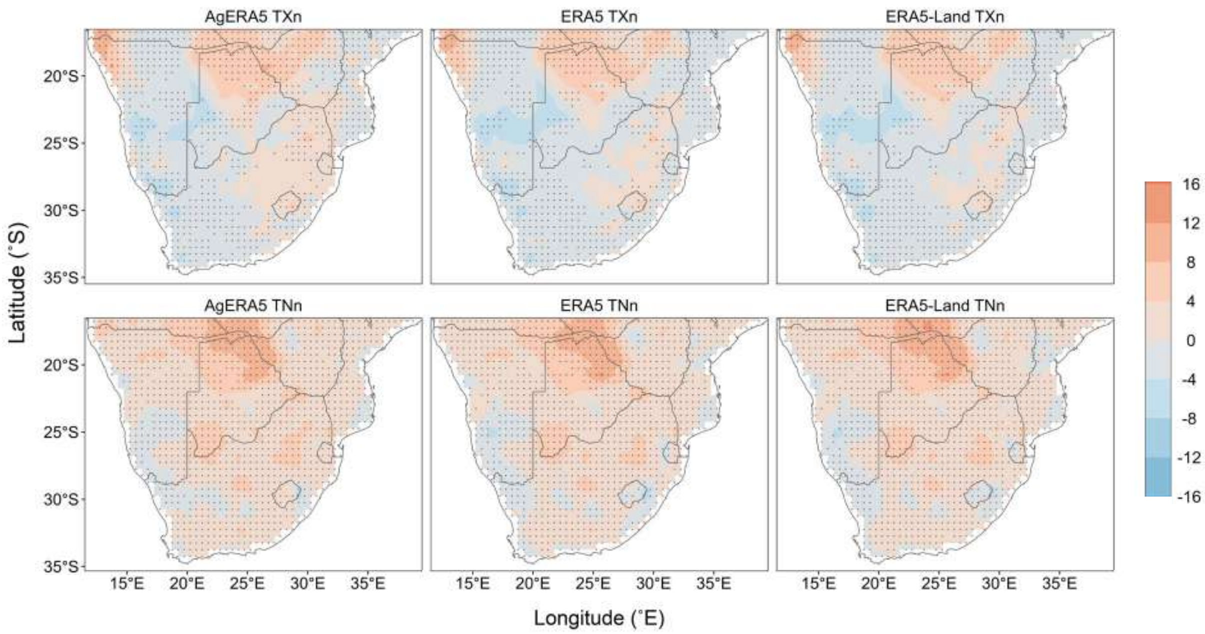

Figure 3.22: Bias maps comparing the NOAA CPC reference dataset with ERA5-based reanalysis products, including AgERA5, ERA5, and ERA5-Land, for June-August values of the coldest day (TXn; °C), and coldest night (TNn; °C) over the period 1979-2021. Stippling indicates statistically significant biases at the 5% significance level ($\alpha = 0.05$).

Figure 3.23 summarises annual mean values of TXn and TNn for each dataset by thermal region (Figure 3.20) over the period 1979-2021 and provides insight into both magnitude differences and temporal correspondence relative to the NOAA CPC reference dataset; see Roffe and Singo (2024) for additional details on the thermal region classifications. Across most thermal regions, the ERA5-based datasets exhibited a systematic warm bias for the magnitude-based indices, with TXn and TNn values typically approximately 1-2 °C higher than those from the reference dataset, a bias that is generally more pronounced for TXn (Figure 3.23). Despite this offset, the time series shows that ERA5-based datasets largely tracked the year-to-year variability of the reference dataset well (Figure 3.23). For TXn and TNn, most thermal regions were characterised by moderate to strong and statistically significant correlations (generally >0.69), indicating good representation of interannual variability (Figure 3.23). However, performance is not spatially uniform. For TXn in thermal regions one and three, correlations are notably weaker, especially from the late 1990s onward, with thermal region one showing very low correlation values ($r \approx 0.05$-0.06; Figure 3.23). These results indicate that while ERA5-based datasets generally perform well in capturing interannual variability of cold temperature indices across most regions, their reliability can be region- and index-dependent, particularly for TXn in warmer, low-elevation thermal regions (Figure 3.23).

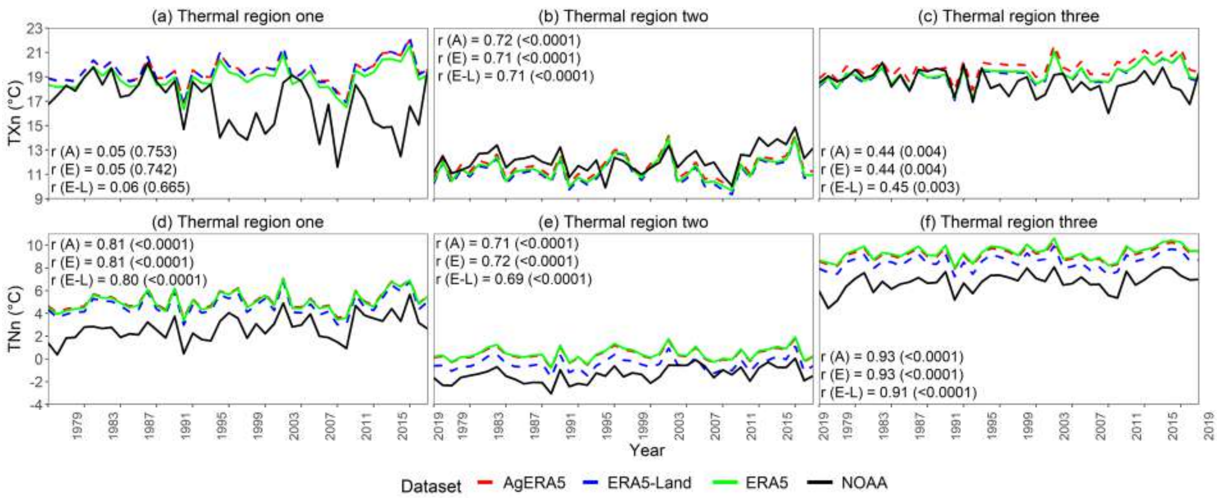

Figure 3.23: Annual mean values of coldest day (TXn) and coldest night (TNn) for each dataset, summarised by thermal region for the period 1979-2021. Spearman rank correlation coefficients (r) and associated p-values (in brackets) are shown for each reanalysis dataset, namely AgERA5 (A), ERA5 (E), and ERA5-Land (E-L), relative to the NOAA CPC reference dataset. Correlations with $p < 0.05$ are statistically significant at the 5% significance level ($\alpha = 0.05$).

Figure 3.24 shows spatial patterns of the Spearman rank correlation between the ERA5-based reanalysis products and the NOAA CPC reference dataset for winter (June-August) values of TXn and TNn over the period 1979-2021. Across all indices and datasets, correlations are uniformly positive and statistically significant over most grid cells, with correlation coefficients generally exceeding 0.3 (Figure 3.24). This indicates that the ERA5-based datasets consistently reproduced the interannual variability of the coldest day and coldest night temperatures across the region. The widespread spatial coherence of the correlations further suggests that these datasets reliably tracked year-to-year changes in extreme cold temperature behaviour relative to the reference dataset. In addition, because correlations were computed using all monthly index values, the results also indicate that the ERA5-based datasets capture intra-annual variability patterns effectively. Overall, these findings demonstrate that, despite biases in absolute magnitudes, the ERA5-based products show strong temporal agreement with the reference dataset for both TXn and TNn, supporting their suitability for analysing variability in cold temperature extremes.

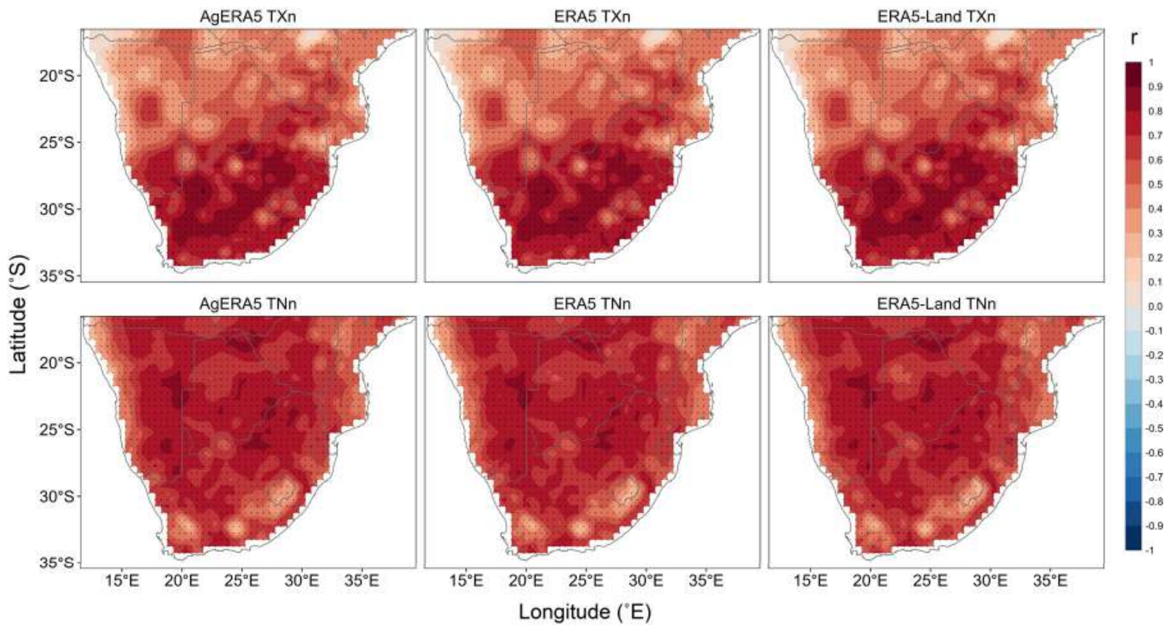

Figure 3.24: Spearman correlation coefficient maps comparing the NOAA CPC reference dataset with ERA5-based reanalysis products, including AgERA5, ERA5, and ERA5-Land, for June-August values of the coldest day (TXn) and coldest night (TNn) over the period 1979-2021. Stippling indicates statistically significant correlations at the 5% significance level (α = 0.05).

Figure 3.25 presents spatial patterns of temporal trends in the coldest day (TXn) and coldest night (TNn) temperatures for the winter season (June-August) over the period 1979-2021, derived from the NOAA CPC reference dataset and the ERA5-based reanalysis products. Overall, the ERA5-based datasets show reasonably good agreement with the reference dataset in terms of the broad direction and magnitude of trends across many regions, suggesting a general ability to capture large-scale changes in winter cold temperature characteristics (Figure 3.25). However, notable discrepancies are evident. For TXn, the ERA5-based datasets do not consistently reproduce the negative trends observed over northern parts of the study region in the reference dataset, with observed trend magnitudes reaching up to approximately -0.4 °C.decade^{-1} (Figure 3.25). Similarly, for TNn, areas characterised by negative trends of up to approximately -0.2 °C.decade^{-1} in the reference dataset are only partially captured or are absent in the ERA5-based products (Figure 3.25). While many grid cells across all datasets exhibit statistically insignificant trends, differences in the spatial extent, sign, and significance of trends highlight ongoing challenges in reliably representing long-term changes in extreme cold temperature characteristics. These results indicate that, although ERA5-based datasets are generally suitable for assessing spatial patterns and variability of cold temperature extremes, caution is warranted when using them to infer local-scale or regional trends in TXn and TNn.

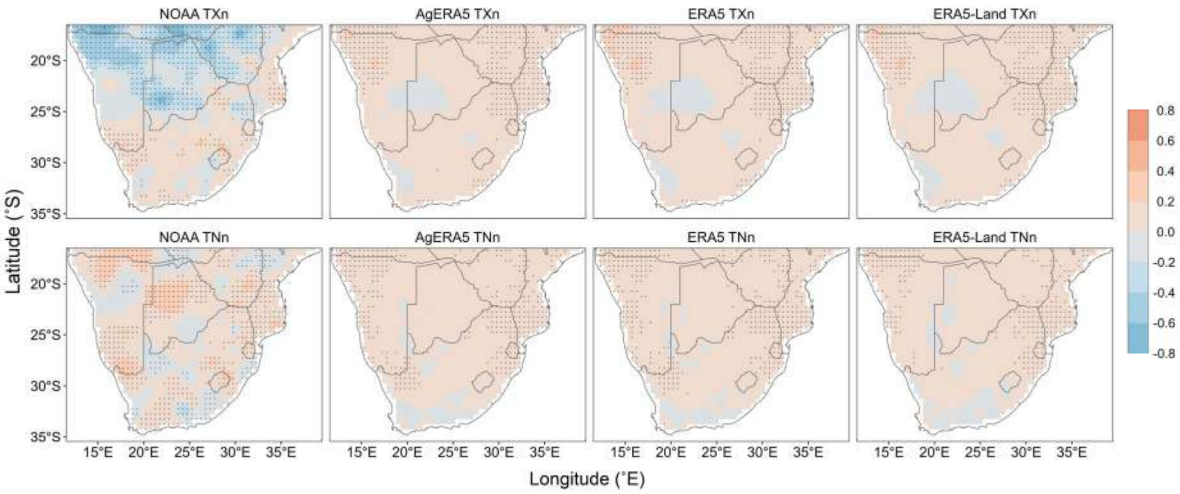

Figure 3.25: Temporal trend maps for the NOAA CPC reference dataset and ERA5-based reanalysis products, including AgERA5, ERA5, and ERA5-Land, showing June-August trends in the coldest day (TXn; °C.decade^{-1}) and coldest night (TNn; °C.decade^{-1}) over the period 1979-2021. Stippling denotes statistically significant trends at the 5% significance level (α = 0.05).

Overall, the results presented in this case study demonstrate that the ERA5-based reanalysis products, including AgERA5, ERA5, and ERA5-Land, are appropriate for characterising the magnitude, spatial structure, and temporal variability of ELTE indices over South Africa. Across both TXn and TNn, the ERA5-based datasets reproduced the large-scale spatial patterns observed in the NOAA CPC reference dataset, including coherent elevation-related gradients, and showed strong temporal correspondence despite the presence of systematic warm biases, particularly for coldest night temperatures. These biases were spatially consistent and therefore do not prevent the use of these datasets for regional-scale assessments of cold temperature magnitudes and variability. However, greater uncertainty is evident in the representation of long-term trends, with discrepancies in trend direction and significance at local scales, indicating that trend-based interpretations should be approached with caution. It is important to note that the results presented here are intended to provide a concise overview relevant to this report, while the cold temperature index evaluation is presented in detail in the conference proceedings by Roffe and Singo (2023), where additional diagnostics, regional analyses, and interpretation are provided. Importantly, this case study provides a clear basis for identifying which ERA5-based datasets can be reliably applied for the computation of extreme cold temperature magnitude indices in subsequent analyses.

3.6 Case study five: extreme low temperature events in the Limpopo River Basin

3.6.1 Introduction

Extreme temperature events are among the most disruptive weather phenomena globally, with impacts including crop damage and livestock losses (Archer et al., 2021; Moeletsi & Tongwane, 2017), infrastructure damage (Mudzingiri et al., 2024), and risks to human health (Roffe et al., 2023). While much of the research on weather and climate extremes in southern Africa has focused on extreme heat and extreme rainfall under a warming climate(Mpungose et al., 2022; van der Walt & Fitchett, 2021), ELTEs have received comparatively less attention, particularly because they are not among the most prevalent weather disasters that occur across South Africa (Bopape et al., 2025), despite their documented impacts. Available evidence indicates that ELTEs will continue to occur over southern Africa under rising temperature scenarios (Iyakaremye et al., 2020), with potentially severe consequences for both natural and human systems. The known impacts of ELTEs highlight the need for improved understanding of their characteristics and drivers, especially at regional scales.

Therefore, this case study examines ELTEs over the Limpopo River Basin (LRB), drawing on work undertaken by Mr Ngwako Mohale as part of his MSc research, which is currently being prepared for publication. The LRB was selected due to its economic importance and its role in supporting diverse livelihoods and agricultural activities (Magombeyi et al., 2016), yet it remains poorly studied in the context of ELTEs despite widely reported impacts. For example, in July 2024, an intense black frost event caused severe damage to potato crops across Limpopo, resulting in substantial supply shortages and anticipated price increases for consumers (Mncwango, 2024). While the broader MSc research investigated ELTEs in depth, including their synoptic drivers, this case study focuses specifically on Tn characteristics and the occurrence and behaviour of ELTEs within the basin, using fine-resolution gridded temperature data (ERA5-Land) that has been shown to perform well over the study region (Roffe & van der Walt, 2023; also see Section 3.5), highlighting the value of gridded datasets for spatially characterising ELTEs.

3.6.2 Data and methodology

This case study uses Tn data from the ERA5-Land reanalysis dataset to examine ELTEs over the LRB for the period 1979-2021. ERA5-Land provides hourly near-surface temperature data at a 0.1° spatial grid resolution (Muñoz-Sabater et al., 2021), which were aggregated to Tn values and clipped to the LRB for the purposes of this analysis.

As an initial analysis step, climatological characteristics of Tn over the LRB were analysed to provide context for the identification and interpretation of ELTEs. This analysis focused on the austral winter season (June-August), representing the period during which ELTEs are known to occur most frequently over southern Africa (Meque et al., 2024b). Climatologies were examined for the full winter season and separately for June, July, and August.

ELTEs were identified using a two-step, spatially explicit approach applied to the winter Tn values. First, for each grid cell, an extreme low Tn was defined as a Tn falling below the grid-cell-specific 10th percentile value of Tn (van der Walt & Fitchett, 2020b; Meque et al., 2024). Second, an ELTE was identified at the basin scale when more than 30% of grid cells within the LRB experienced extremely low Tn on the same day. This approach enabled the identification of spatially coherent basin-scale events rather than isolated local extremes.

Characteristics of ELTEs were subsequently analysed, including their frequency, duration, and magnitude (van der Walt & Fitchett, 2020b; Meque et al., 2024). A composite of Tn anomalies was also calculated for identified events to assess the severity of cold conditions relative to the winter climatology. Temporal trends in both winter seasonal and monthly Tn characteristics and ELTE metrics were evaluated using the non-parametric Mann-Kendall trend test (statistical significance at the 5% alpha level), with trend magnitude quantified using Sen's slope estimator (van der Walt & Fitchett, 2020b; Meque et al., 2024).

3.6.3 Results and discussion

3.6.3.1 Daily minimum temperatures: climatologies and temporal trends

Figure 3.26 shows the spatial distribution of mean Tn for the winter season (June-August) and for individual winter months (June, July, and August) over the LRB for the period 1979-2021. Across all months and for the full winter season, a consistent spatial pattern occurred, with lower Tn generally occurring over higher-elevation areas of the basin and warmer Tn typically occurring over lower-lying regions (Figure 3.26). Winter Tn values were typically below approximately 7 °C in elevated areas, while values in lower-elevation regions commonly exceeded 10 °C and reached up to around 16 °C in places (Figure 3.26). Clear intra-seasonal differences are also apparent, with July emerging as the coldest winter month across most of the basin, characterised by the most extensive areas of low Tn values, while August was consistently the warmest of the three winter months (Figure 3.26). These results highlight the strong influence of topography on Tn patterns within the basin and provide important context for understanding the spatial and temporal characteristics of ELTEs examined in subsequent analyses.

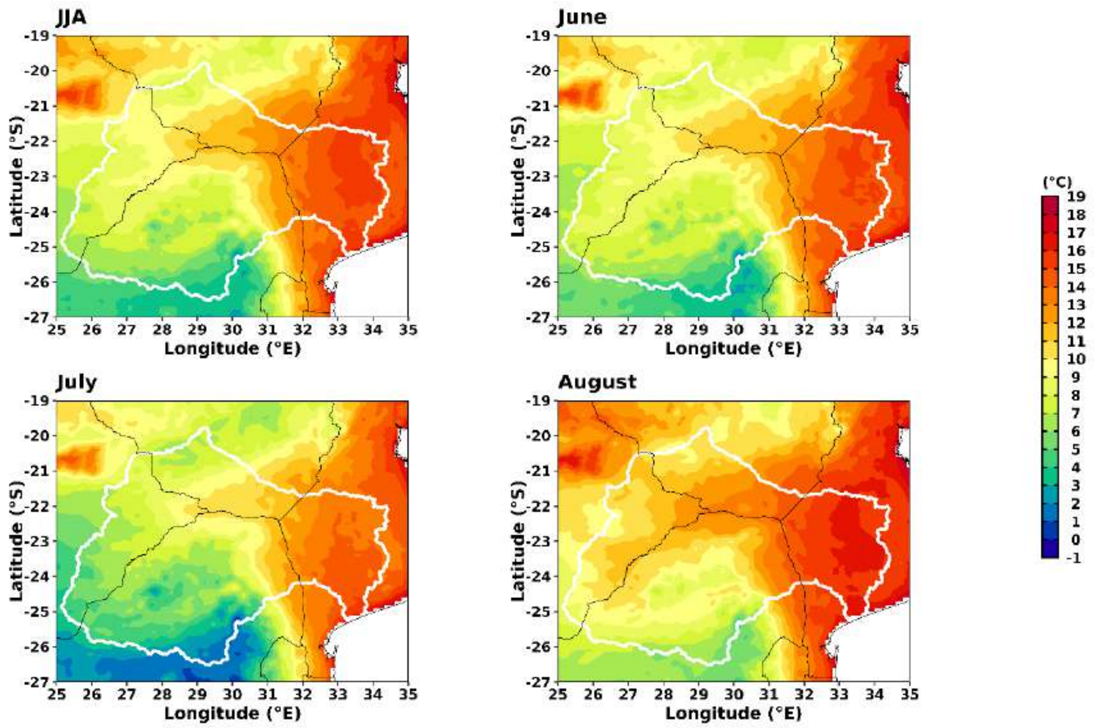

Figure 3.26: Maps showing the seasonal mean minimum temperature (Tn) for winter (June-August) and the monthly mean Tn for June, July, and August over the Limpopo River Basin (LRB) for the period 1979-2021. The white polygon delineates the boundary of the LRB.

Figure 3.27 shows spatial patterns of temporal trends in Tn over the LRB for the winter season (June-August) and for individual winter months over the period 1979-2021. Across the basin, Tn values were characterised by predominantly increasing trends in almost all instances, indicating a clear warming signal in winter Tn (Figure 3.27). For the seasonal and June trend maps, statistically significant warming was widespread across much of the basin, with trend magnitudes generally reaching up to approximately 0.30 °C.decade^{-1}, and locally higher values were evident in the southern parts of the basin (Figure 3.27). July exhibited the weakest warming signal, with trend magnitudes typically below 0.20 °C.decade^{-1} and more spatially limited areas of statistical significance (Figure 3.27). In contrast, August showed a stronger and more spatially coherent warming pattern, similar to that observed for the June and seasonal trends (Figure 3.27). These results indicate that winter minimum temperatures over the LRB have increased over recent decades, with the strongest and most consistent warming occurring in early and late winter, providing important context for the evolving characteristics of ELTEs in the region.

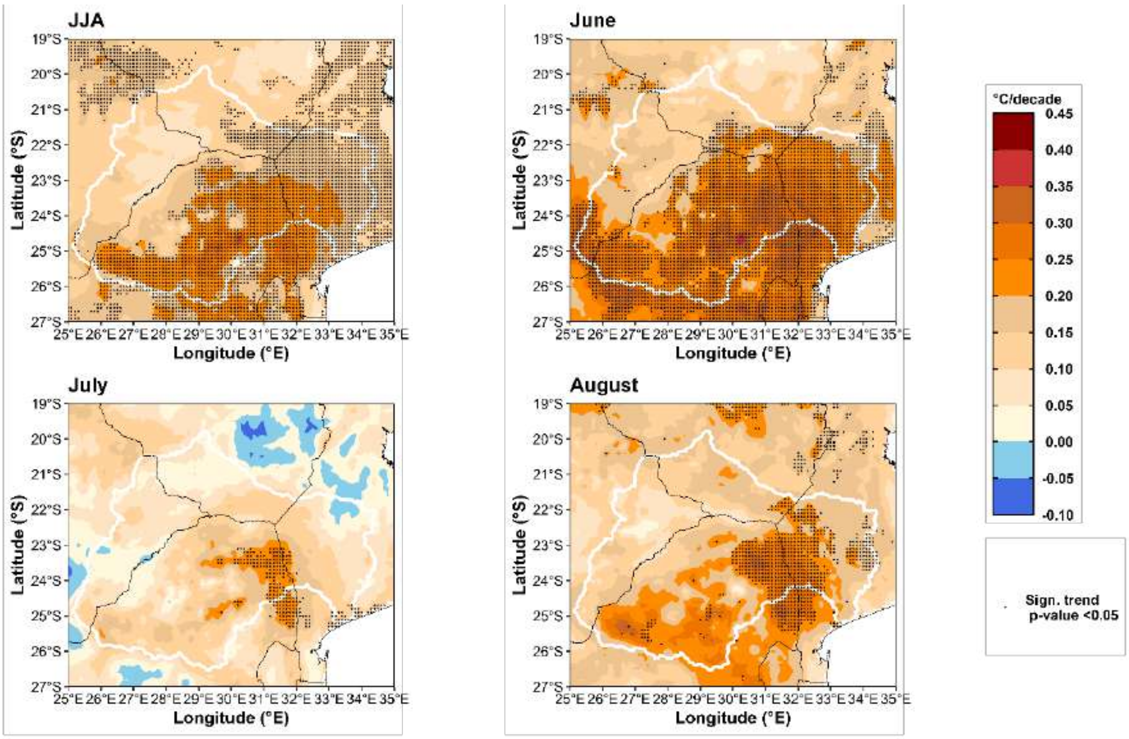

Figure 3.27: Maps showing the spatial distribution of minimum temperature (Tn) trends per decade for the winter season (June-August) and for the individual months of June, July, and August over the Limpopo River Basin (LRB) for the period 1979-2021. The white polygon delineates the LRB boundary, while stippling indicates statistically significant trends ($p < 0.05$).

3.6.3.2 Characteristics of extreme low temperature events

Figure 3.28 shows the duration of ELTEs identified over the LRB for the period 1979-2021, with events ordered chronologically by occurrence. The results indicate that most ELTEs were short-lived, with many events lasting only one or two days, with 68 and 27 of these events, respectively, out of 132 ELTE events (Figure 3.28). This highlights the predominantly episodic nature of extreme low temperature conditions in the basin. Longer-duration events occur much less frequently, with the longest event persisting for 11 days, followed by a small number of events lasting 9 and 8 days (Figure 3.28). Although rare, these multi-day events represent periods of sustained cold conditions that are likely to have more severe impacts than shorter events. Overall, the distribution of event durations suggests that while ELTEs in the LRB are typically brief, occasional prolonged cold events do occur and contribute disproportionately to cold-related risk in the region.

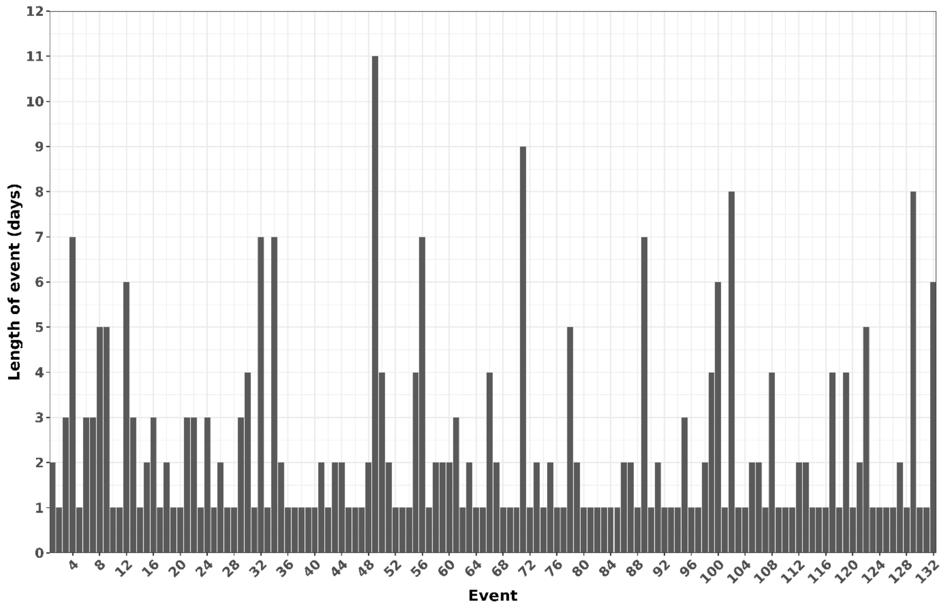

Figure 3.28: Graph showing extreme low temperature events (ELTEs) identified over the Limpopo River Basin (LRB) for the period 1979-2021. Events are ordered chronologically by occurrence, with the first event in the record labelled as Event 1 and the final event as Event 132. Bars indicate the lifespan (duration) of each ELTE.

Figure 3.29 shows the distribution of ELTEs across the winter months over the LRB for the period 1979-2021. The results indicate a clear seasonal concentration of ELTEs in mid-winter, with July having recorded the highest number of events (69), followed by June with 48 events (Figure 3.29). In contrast, August was characterised by substantially fewer events, with only 15 ELTEs identified over the full record (Figure 3.29). This pattern is consistent with July having represented the coldest winter month across the basin, while August marked a transitional period toward warmer spring conditions (Figure 3.26). The strong mid-winter dominance of ELTE occurrence highlights the heightened vulnerability of the basin to extreme cold conditions during July in particular.

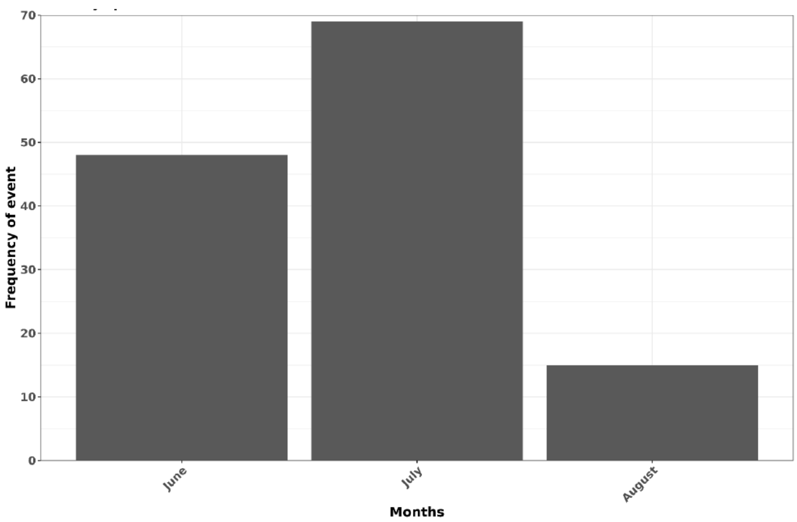

Figure 3.29: Graph showing the frequency of extreme low temperature events (ELTEs) per winter month over the Limpopo River Basin (LRB) for the period 1979-2021.

Figure 3.30 shows spatial patterns of Tn anomalies during ELTEs over the Limpopo River Basin for the period 1979-2021, relative to the winter seasonal climatology. During ELTEs, Tn values were substantially lower than average, with anomalies reaching up to approximately -5 °C across parts of the basin (Figure 3.30). The strongest negative anomalies are concentrated over the southwestern areas of the basin, particularly in regions characterised by higher elevation and more southerly latitudes (Figure 3.30). In contrast, northeastern areas exhibited weaker cold anomalies, typically not exceeding -3 °C (Figure 3.30). This spatial pattern indicates that ELTE intensity varies considerably across the basin, with topography and latitude playing an important role in amplifying cold extremes. These results highlight that, although ELTEs affect the entire basin, their severity is greatest in elevated and southern regions, where departures from average winter conditions are most pronounced.

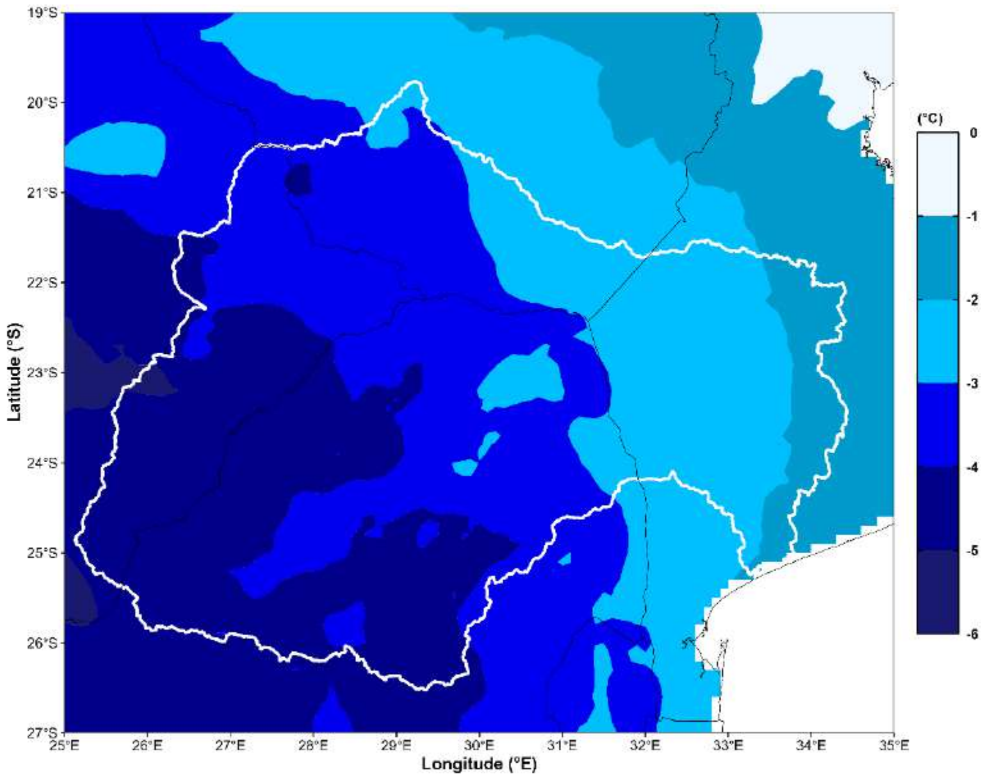

Figure 3.30: Map showing daily minimum temperature (Tn) anomalies during extreme low temperature events (ELTEs) in the Limpopo River Basin (LRB) for the period 1979-2021. The white polygon shows the borders of the LRB region.

Figure 3.31 summarises interannual variability and trends in the frequency, duration, and magnitude of ELTEs over the LRB for the period 1979-2021. Considerable year-to-year variability was evident across all three characteristics (Figure 3.31). Annual ELTE frequency ranged from years with no events (e.g., 1986, 1998-1999, and 2017-2019) to a maximum of 10 events in 2011 (Figure 3.31). The annual mean duration of ELTEs similarly varied, with some years characterised by short-lived events averaging around one day (e.g., 1984, 1991, 1993, 1995, 2006, 2008, and 2015), while the longest average duration, approximately five days, occurred in 2001 (Figure 3.31). Event magnitude also fluctuated over time, with annual mean Tn values associated with ELTEs having ranged from approximately 2.75 °C in 2008 to about 2.95 °C in 1985 (Figure 3.31). Although linear trends suggest decreases in ELTE frequency (-0.13 events.year^{-1}), duration (-0.16 days.year^{-1}), and magnitude (-0.22 °C.year^{-1}; Figure 3.31), none of these trends were statistically significant (p = 0.252, 0.141, and 0.061, respectively). This indicates that, despite a warming background climate, for 1979-2021, ELTE characteristics over the basin remain highly variable from year to year, with no robust long-term decline in occurrence or persistence detectable over the study period.

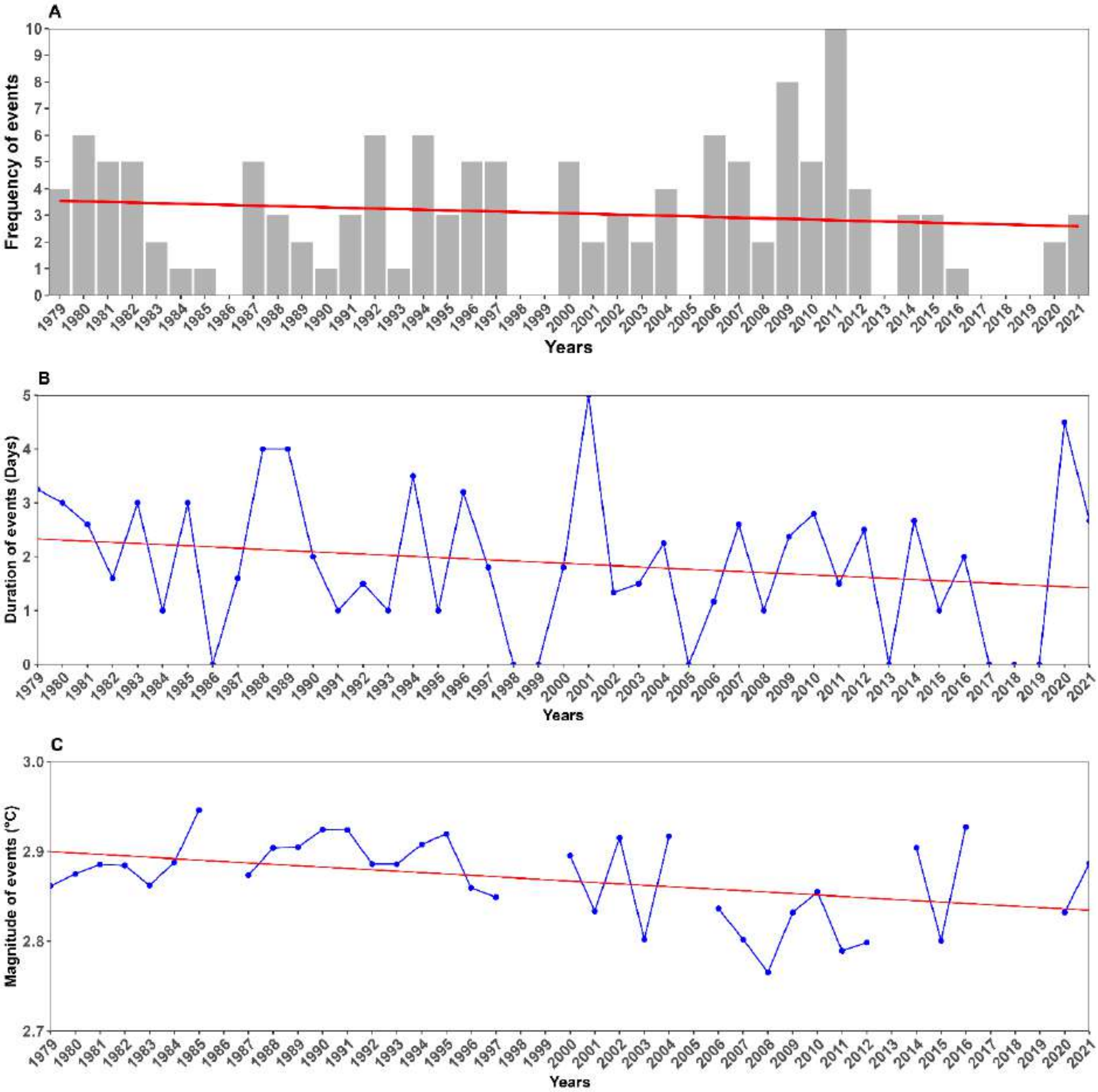

Figure 3.31: Graphs showing A) the annual occurrence of extreme low temperature events (ELTEs) over the Limpopo River Basin (LRB) for the period 1979-2021, B) the annual mean duration of ELTEs, and C) the annual mean minimum temperature (Tn) associated with ELTEs. Years with no recorded ELTEs are excluded from the analysis or denoted by a zero for plot B. Red lines indicate linear trend lines in each panel.

3.6.3.3 Summary

Overall, the results from this case study provide a coherent picture of the characteristics and evolution of ELTEs over the LRB during the period 1979-2021. Winter Tn values across the basin exhibited strong and consistent spatial structure, with colder conditions concentrated in higher-elevation and more southerly areas, and July emerging as the coldest winter month. Despite widespread and statistically significant warming trends in winter Tn values, particularly during June and August, ELTEs continued to occur regularly across the basin. Most ELTEs were short-lived, typically lasting one to two days, although occasional multi-day events persisted and represented periods of heightened cold risk. ELTE occurrence was strongly concentrated in mid-winter, with July accounting for most ELTEs, consistent with the seasonal Tn climatology. Spatial patterns of ELTE intensity further showed that cold anomalies during events can be substantial, reaching up to approximately -5 °C relative to the winter mean Tn, particularly over higher-elevation and southern parts of the basin. While interannual variability in ELTE frequency, duration, and magnitude is pronounced, no statistically significant long-term trends were detected in these characteristics, indicating that year-to-year variability remains the dominant feature of ELTE behaviour. Collectively, these results highlight that, although the basin experienced winter warming, ELTEs remained an important and persistent feature of the regional climate, with implications for climate-sensitive sectors such as agriculture and livelihoods. Moreover, these results demonstrate the value of using climate indices to move beyond mean temperature analyses, enabling a more nuanced and impact-relevant understanding of extreme cold conditions and their spatiotemporal characteristics.

3.7 Synthesis and key conclusions

Across the five case studies, the chapter demonstrates how rainfall- and temperature-based climate indices can be computed and interpreted to characterise climate variability, extremes, and sector-relevant impacts in South Africa, while also highlighting how outcomes depend on dataset choice, spatial scale, and methodological decisions. Collectively, the applications illustrate the value of indices as interpretable summary measures that translate complex daily climate information into metrics aligned with agricultural and water-relevant stressors, while reinforcing that index-based conclusions must be evaluated considering underlying data quality and representativeness.

A consistent finding across the case studies is that indices often capture coherent physical signals even when derived from different data sources, particularly with respect to interannual variability and broad spatial gradients. For example, heavy rainfall-day indices derived from ERA5-based datasets reproduce the large-scale west-east frequency gradient and show moderate to strong temporal correspondence with station-based variability at many locations, while ERA5 precipitation over the Vaal WMA closely tracks year-to-year and seasonal variability relative to CRU despite a systematic wet bias in absolute magnitude. Similarly, ERA5-based temperature datasets reproduce the broad spatial structure of cold temperature indices and exhibit strong temporal agreement with reference datasets across much of South Africa, supporting their use for analysing variability and spatial patterns of extreme conditions at regional scales.

At the same time, the evaluation-focused case studies demonstrate that magnitude-based interpretation is where limitations become most consequential, particularly for threshold and extreme indices. For heavy rainfall days (R10mm and R20mm), ERA5-based datasets tend to underestimate event frequencies, meaning that absolute counts and local exceedance metrics require careful interpretation and, where necessary, additional bias assessment. For cold temperature indices, systematic warm biases, especially for coldest-night temperatures, indicate that gridded products may under-represent the severity of extreme cold at specific locations. These findings highlight a key distinction for applied use: gridded datasets are generally well suited for examining relative variability, spatial structure, and large-scale signals, but greater caution is required when indices are used to quantify absolute extremes, local thresholds, or site-specific trends.

The applied agricultural case study further illustrates how climate indices provide a practical bridge between climate information and observed impacts, while underscoring the complexity of attribution. For maize production, rainfall- and PET-based indices show the clearest and most consistent relationships with yield variability, with temperature acting largely as a compounding stressor during dry conditions. For cattle production, summer temperature and thermal comfort indices display a coherent negative association with cattle population change, consistent with heat stress impacts, while winter relationships are weaker and likely moderated by management responses. These results demonstrate how indices linked to moisture availability and thermal stress can contextualise agricultural variability without implying deterministic thresholds.

Importantly, the LRB case study extends this interpretation beyond seasonal summaries by illustrating how index-based approaches can be used to identify, characterise, and contextualise discrete extreme events. Despite widespread winter warming trends, ELTEs continue to occur regularly, are often spatially coherent at the basin scale, and can be both intense and episodic. This highlights the value of event-based indices for capturing residual climate risk that is not evident from mean conditions alone and reinforces the importance of monitoring cold extremes alongside broader warming trends, particularly in climate-sensitive agricultural and livelihood systems.

Finally, the Vaal WMA case study illustrates how relatively simple rainfall indices and seasonal diagnostics can reveal changes not only in rainfall amounts but also in the timing and organisation of precipitation. The dominance of declining trends in early and extended summer rainfall, contrasted with weak late summer increases, suggests a potential reorganisation of seasonal rainfall rather than a uniform drying signal, with direct implications for water availability and climate risk management. Overall, the chapter demonstrates that climate indices offer a defensible and flexible framework for summarising climate conditions across diverse applications in South Africa, provided that their interpretation explicitly accounts for dataset limitations, scale dependence, and the distinction between variability-focused and magnitude-focused analyses. These are considerations that are central to the responsible operational use of indices within the Weather Risk app.

Chapter 4: Integrating stakeholder consultations and questionnaire responses into the user-centred design of the web-based Weather Risk app

4.1 Introduction

The development of effective WCSs for agriculture requires more than scientifically robust data products (Moeletsi et al., 2013; Hansen et al., 2019; Vaughan et al., 2019; Walker, 2020; Moeletsi & Tsubo, 2024). Instead, it depends critically on how well such services reflect the needs, decision contexts, and capacities of intended users (Moeletsi et al., 2013; Hansen et al., 2019; Vaughan et al., 2019; Walker, 2020; Moeletsi & Tsubo, 2024). Despite increasing availability of weather and climate information in South Africa, uptake in agricultural decision-making remains uneven, particularly due to challenges related to accessibility, interpretability, and relevance for operational planning and risk management (Lumbroso et al., 2024; Moeletsi & Tsubo, 2024). These challenges have highlighted the importance of co-development approaches that actively involve stakeholders in shaping WCSs, ensuring that information products are both scientifically credible and practically usable (Moeletsi & Tsubo, 2024).

User-centred and participatory design approaches are particularly important for agrohydrometeorological applications, where users include farmers, extension officers, advisors, researchers, and policymakers operating across diverse production systems and climatic regions (Moeletsi & Tsubo, 2024). These groups differ in their technical backgrounds, decision horizons, and information requirements, yet they frequently rely on the same underlying weather and climate information (Walker, 2020). Structured stakeholder engagement enables developers to identify priority indices, appropriate temporal and spatial scales, preferred modes of information delivery, and usability considerations, thereby supporting the development of decision-support tools that are better aligned with real-world agricultural needs (Meadow et al., 2015; Wall et al., 2017).

This chapter documents how stakeholder consultations and questionnaire-based feedback were integrated into the user-centred design of the Weather Risk app developed under this project. It focuses on how stakeholder input informed key design decisions, including the selection of agrohydrometeorological indices, the emphasis on short-term weather and water availability information, and the incorporation of usability considerations within the web-based platform. The central message of this chapter is the importance of co-development in the design of WCSs intended to support agricultural and food security decision-making.

The primary evidence base informing this chapter is drawn from Myeni and Roffe (2025), which analysed responses from a national online questionnaire disseminated to stakeholders involved in weather- and climate-related activities across South Africa. That study examined climate change awareness, as well as the accessibility, use, and challenges associated with WCSs across multiple sectors, including environment and natural resources, water resources, disaster management, economic development and urban planning, human health, and agriculture and food security. In this chapter, only results related to the accessibility, use, and challenges associated with WCSs for the agriculture and food security sector are considered, as these findings were directly applicable to the development of the Weather Risk app, aligning with the mandate of the ARC. In addition, this chapter incorporates results from a stakeholder focus group meeting held in Tzaneen (Limpopo) on 11 October 2023, which brought together stakeholders who use or support the use of weather and climate information. This engagement provided an opportunity to test and refine the questionnaire, introduce the concept of the climate and water availability indices app, and obtain direct feedback on information needs and index preferences. Insights from both the national questionnaire and the Tzaneen stakeholder engagement were used to inform the user-centred design of the Weather Risk app. By contributing to the development of the Weather Risk app, this chapter contributes to addressing Objective 3 of this research project.

4.2 Data and methodology

Stakeholder engagement undertaken to inform the user-centred design of the Weather Risk app consisted of two complementary components. This included a focus group discussion meeting and a national-scale online questionnaire.

The first component involved a focus group discussion meeting hosted on 11 October 2023 in Tzaneen (Limpopo) at the Hotel@Tzaneen conference venue. The primary aim of this engagement was to bring together stakeholders who use, or support the use of, weather and climate information, and to gain insight into how such information and climatic indices are currently accessed, interpreted, and applied in practice. During the meeting, participants were provided with background on the overall project and introduced to the concept of the Weather Risk app. Structured group discussions were held to obtain feedback on information needs, index relevance, and expectations from the proposed system. Participants also completed the questionnaire used in the second engagement component, allowing for initial testing and refinement of the questionnaire instrument. Photographs from this engagement activity are shown in Figure 4.1.

The second component comprised the collection of responses from a national online questionnaire (still open to the public via https://forms.gle/vume1JRK3DG77RP67), the methodology of which is detailed in Myeni and Roffe (2025) The questionnaire targeted stakeholders across South Africa who engage with WCSs and captured information related to climate change awareness, as well as the accessibility, use, and challenges associated with weather and climate information. While the published study reports results across multiple sectors, only responses relevant to the agriculture and food security sector are considered in this chapter, as the primary audience of the Weather Risk app was intended to be stakeholders across the agricultural sector.

Figure 4.1: Photographs from the stakeholder engagement activity undertaken on 11 October 2023 in Tzaneen (Limpopo) at the Hotel@Tzaneen conference venue. The top panel shows the attendees, and the bottom panel shows the presentation of the background to the overall Water Research Commission (WRC) project.

4.3 Results and discussion: in-person stakeholder consultations

The stakeholder engagement held in Tzaneen (Limpopo) on 11 October 2023 provided qualitative insights into how weather and climate information is accessed, interpreted, and applied by stakeholders operating across a range of sectors. Based on the attendance register, participants represented a broad cross-section of institutions, including the Limpopo Provincial Disaster Management Centre, Mopani District Municipality Disaster Management Centre, Greater Tzaneen Municipality, Limpopo Department of Agriculture and Rural Development, Limpopo Department of Water and Sanitation, Letaba Water Users Association, the Department of Health (Tzaneen Malaria Control Programme), and African Realty Trust. This diversity of participants highlighted the wide range of decision contexts in which weather and climate information is used, extending beyond agriculture alone to include water management, disaster risk management, health, and municipal planning.

Following an introduction to the project, participants were invited to introduce themselves and describe how they currently use weather and climate information in their work, as well as whether and how they make use of weather/climatic indices. Discussions indicated that participants engage with weather and climate information for a variety of purposes, including short-term operational planning, risk preparedness, monitoring of rainfall and temperature conditions, water resource management, and early warning for weather- and climate-related hazards. Several participants noted challenges associated with interpreting raw weather data or technical indices, reinforcing the need for information products that are easy to understand and directly applicable to decision-making.

Participants were then introduced to the concept of the Weather Risk app, including its intended purpose and the types of weather and water availability indices it would provide. This was followed by open discussion, during which participants provided feedback on the types of information they would find most useful, how such information should be presented, and how it could support their respective roles. Feedback emphasised the value of short-term weather information, clear visualisation of indices, and the ability to relate weather conditions to practical decisions such as agricultural activities, water management actions, and disaster preparedness. Importantly, discussions also highlighted the need for information to be accompanied by advisory-type messages or interpretive guidance, rather than being presented as data alone, to support more effective decision-making. The discussions further underscored the role of intermediaries, such as extension officers and municipal or sectoral officials, in translating weather and climate information for end users.

The final component of the engagement involved participants completing the questionnaire that was later disseminated nationally. This provided an opportunity to test the questionnaire in a facilitated setting and to identify aspects requiring clarification or refinement. Feedback from participants highlighted the need to simplify wording in some questions, clarify terminology that could be interpreted differently across sectors, and ensure that response options were clearly aligned with the intent of each question. These refinements were implemented prior to the wider dissemination of the questionnaire. Insights from the Tzaneen focus group discussions and the refined questionnaire responses were subsequently used to inform the prioritisation of indices, usability considerations, and design choices incorporated into the Weather Risk app.

4.4 Results and discussion: online questionnaire responses

4.4.1 Respondent profile and organisational context

Table 4.1 summarises the demographic characteristics and organisational affiliations of respondents from the agriculture and food security sector. Respondents represented a wide range of organisations and institutions involved in agricultural production, research, advisory services, and sectoral support. The largest proportion of respondents were from national or provincial departments of agriculture (40.5%), followed by respondents from the ARC Council (14.3%) and universities (9.5%; Table 4.1). Additional respondents represented private agricultural enterprises, producer organisations, consulting firms, research entities, and self-employed practitioners (Table 4.1). This institutional spread highlights that users of weather and climate information within the agricultural sector extend beyond primary producers to include a broad network of intermediaries and support organisations that play a role in advising, planning, and decision-making.

Table 4.1: Demographic and organisational characteristics of respondents from the agriculture and food security sector.

Group	Number of respondents (%)
Organisation / Institution / Workplace	
National or Provincial Department of Agriculture	40.5
Agricultural Research Council (ARC)	14.3
University	9.5
Radical Seedlings cc	4.8
African Realty Trust	2.4
AgriSA	2.4
Agulhas Honeybush Tea	2.4
ASSET research	2.4
Capespan	2.4
Karan Beef Pty Ltd	2.4
MBB Consulting Engineers	2.4
Self-employed	2.4
Strandveld Wines Pty Ltd	2.4
Thoroyalunonya Pty Ltd	2.4
Universal Leaf South Africa	2.4
Witvlei Apple Farms Pty Ltd	2.4
ZZ2	2.4
Gender	
Female	69.0
Male	31.0
Education	
Grade 11-12	2.4
Diploma	4.8
University undergraduate	19.0
University postgraduate	73.8
Experience	
0-4 years	16.7
5-9 years	21.4
10-14 years	11.9
15-19 years	21.4
20-24 years	11.9
25-29 years	9.5
More than 30 years	7.1

In terms of individual characteristics, the respondent group was predominantly female (69%), with males comprising 31% of respondents (Table 4.1). Most respondents reported relatively high levels of formal education, with nearly three-quarters (73.8%) holding a postgraduate qualification and a further 19% holding an undergraduate university degree (Table 4.1). Respondents also reflected a wide range of professional experience, with representation across early career (0-4 years) to highly experienced professionals (more than 30 years; Table 4.1). Together, these characteristics indicate that WCSs are used by individuals with varying levels of experience and expertise, reinforcing the need for information products that are both technically robust and accessible to users with different backgrounds and roles within the agricultural sector.

4.4.2 Perceived climatic risks influencing agriculture and food security

Across respondents from the agriculture and food security sector, an overwhelming majority (95%) indicated that climate change is already affecting, or is expected to affect, their current or future work activities. This result, while not shown graphically, provides important context for understanding respondents' perceptions of climatic risk and their demand for weather and climate information.

Figure 4.2 illustrates the specific climatic risks identified by respondents as most relevant to the agriculture and food security sector. The most frequently cited risk was reduced agricultural productivity or suitability and degradation of agricultural land (45%; Figure 4.2). This was followed by risks related to water availability, quality, and management (19%), reduced rainfall and drought conditions (19%), increased extreme rainfall and flooding (17%), and increased temperatures or extreme temperature events (14%; Figure 4.2). While many of these risks reflect longer-term climatic changes, they manifest through short-term weather extremes and variability, which are the primary focus of the Weather Risk app. In particular, the prominence of water-related risks informed the inclusion of water availability indicators within the app, with an emphasis on variables and indices most relevant to short-term planning and decision-making, rather than broader water quality or governance aspects. These findings underscore the importance of WCSs that address short-term risks while remaining cognisant of longer-term climatic trends shaping agricultural systems. More broadly, results from the national questionnaire indicated that different sectors are influenced by different climatic risks, reinforcing the need for sector-specific approaches to WCS design. The focus on agriculture and food security in this chapter, therefore, reflects the distinct risk profile and information needs of this sector, which directly informed the prioritisation of indices and functionalities incorporated into the Weather Risk app.

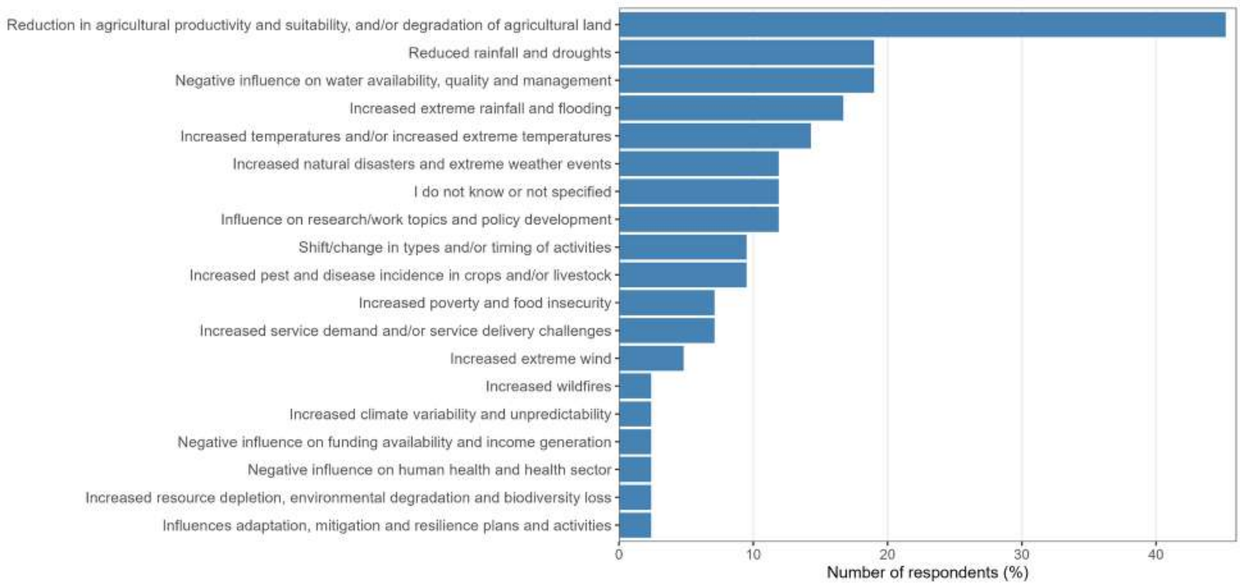

Figure 4.2: Perceived climatic risks influencing the agriculture and food security sector, as identified by respondents.

4.4.3 Access to and use of weather and climate services (WCSs)

Having established the need for sector-specific WCSs, this section examines how respondents from the agriculture and food security sector currently access and use such services. Most respondents (95%) reported having access to WCSs, and all respondents with access indicated that these services are actively used (Figure 4.3). While not included as a visual result, the most common means of accessing WCSs was via the Internet (75%), highlighting digital platforms as a key delivery mechanism for weather- and climate-related information within the sector. This finding supports the use of a web-based platform for the Weather Risk app.

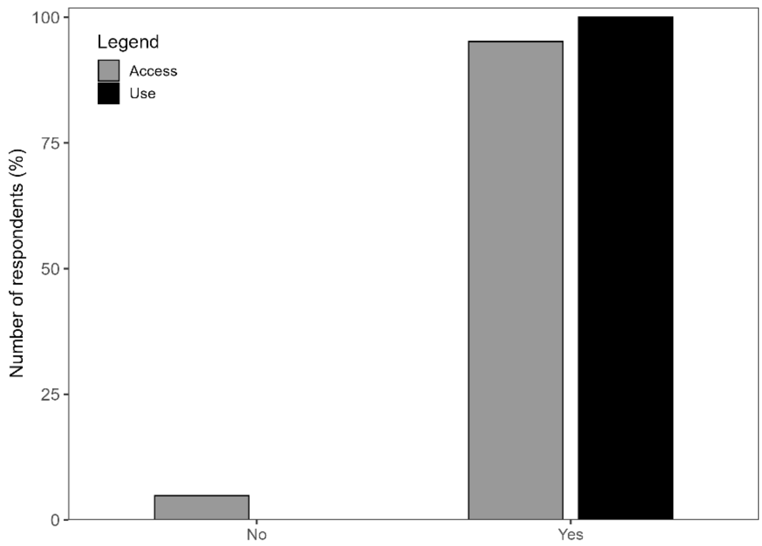

Figure 4.3: Access to weather and climate services (WCSs) within respondents' organisations/institutions/workplaces, and whether these services are actively used.

Respondents reported that they primarily access and use forward-looking WCSs (Figure 4.4). These included seasonal forecasts (58%), early warning systems (53%), and daily to seven-day weather forecasts (50%; Figure 4.4). The prominence of forecast-based services reflects the importance of anticipatory information for agricultural planning and management decisions, and reinforces the relevance of incorporating short-range weather forecasts into the Weather Risk app.

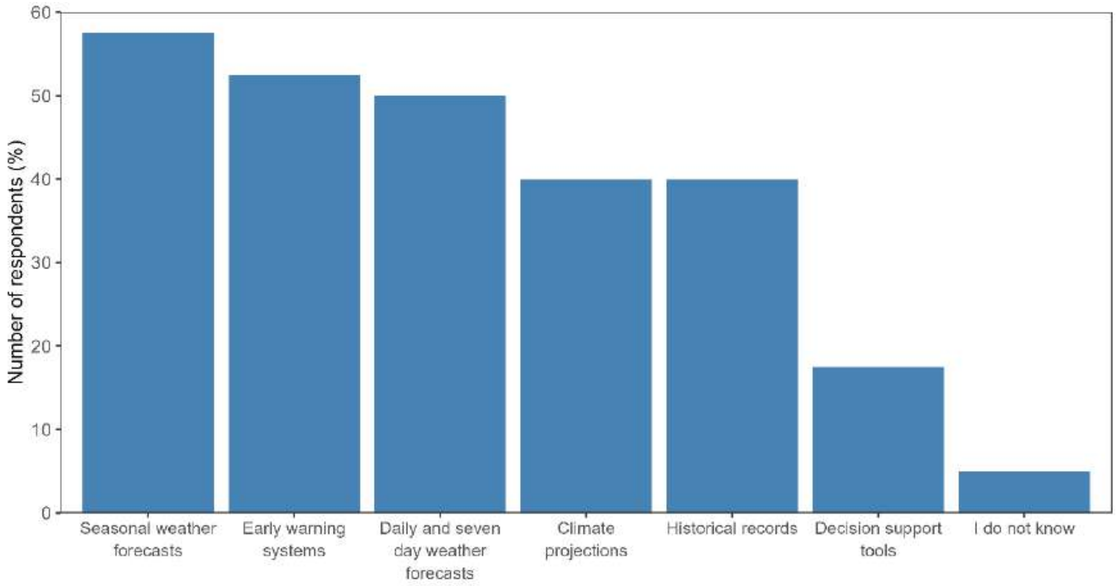

Figure 4.4: Types of weather and climate services (WCSs) accessed and used by respondents' organisations/institutions/workplaces.

In terms of frequency of use, respondents indicated regular engagement with WCSs, with daily (55%), monthly (53%), and weekly (28%) use most reported (Figure 4.5). This high frequency of access underscores the central role of weather and climate information in agricultural decision-making and highlights the need for information products that provide fine temporal resolution. In support of the Weather Risk app design, these findings motivated the inclusion of daily to monthly summarised indices, as discussed further in Section 5.3.2 and Section 5.4.

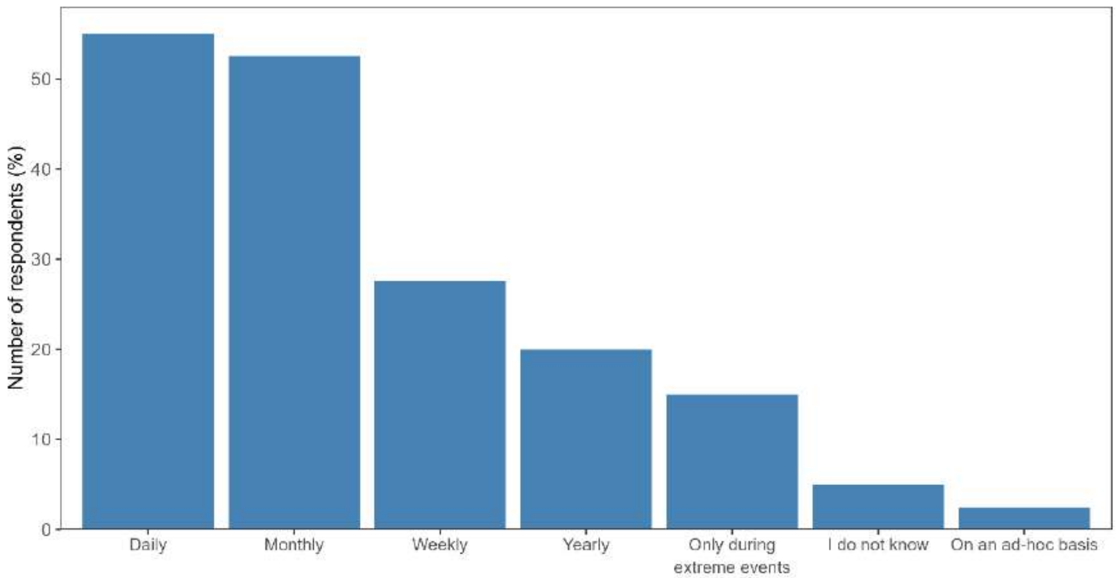

Figure 4.5: Frequency with which respondents' organisations/institutions/workplaces use weather and climate services (WCSs).

To better understand the drivers of frequent use, respondents were also asked about the purposes for which WCSs are used (Figure 4.6). The most reported purposes included informing planning and decision-making (78%), risk management (70%), development of adaptation and mitigation strategies (68%), research activities (53%), and natural resource management (53%; Figure 4.6). These results demonstrate the wide-ranging applications of WCSs within the agriculture and food security sector and highlight the need for a flexible information platform capable of supporting multiple decision contexts.

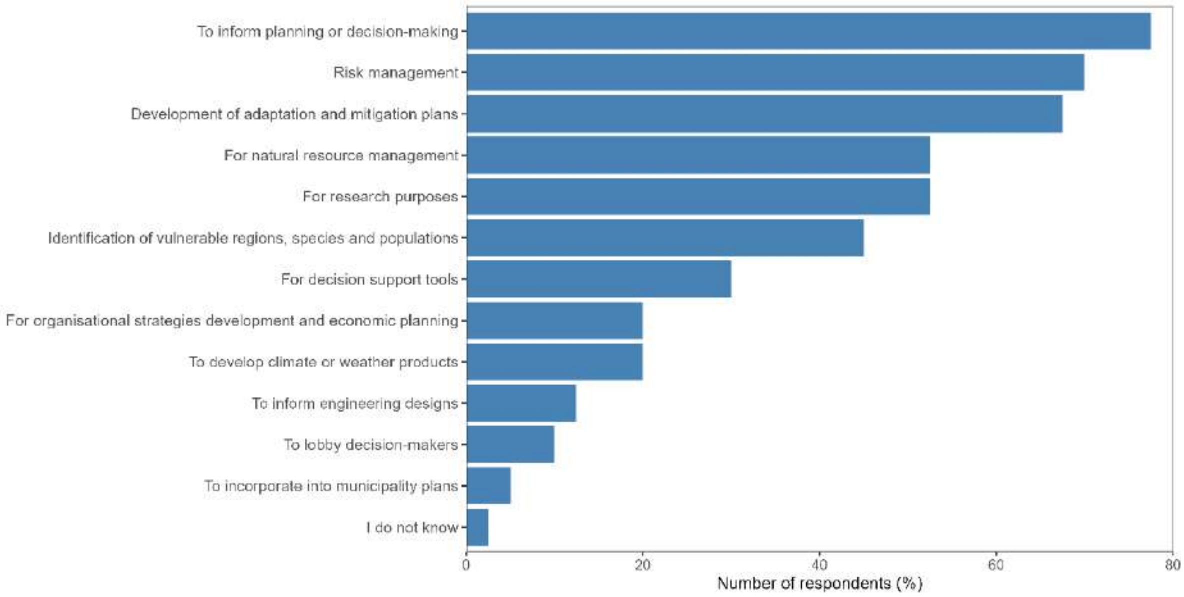

Figure 4.6: Primary purpose for which weather and climate services (WCSs) are used within respondents' organisations/institutions/workplaces.

Given the diversity of purposes identified, particular attention was given to how weather and climate information is presented. The use of climate indices was explored, as indices translate daily weather and climate data into metrics that are more readily interpretable and decision-relevant. Respondents reported frequent use of rainfall-based indices (90%), indices related to extreme weather events (80%), temperature-based indices (55%), fire indices (35%), and water availability and quality indices (28%; Figure 4.7). These results directly informed the design of the Weather Risk app. While the initial concept focused primarily on rainfall and temperature indices, as emphasised by the literature review under Section 2.2, the findings indicated a clear need for a broader suite of indices relevant to agricultural decision-making. Consequently, as outlined in Section 5.3.2, the app incorporates a wider range of weather indices, including fire indices, PET indices, thermal comfort indices, and wind-related indices. The selection of indices was further guided by the availability of variables recorded within the ARC weather station network (Moeletsi et al., 2022).

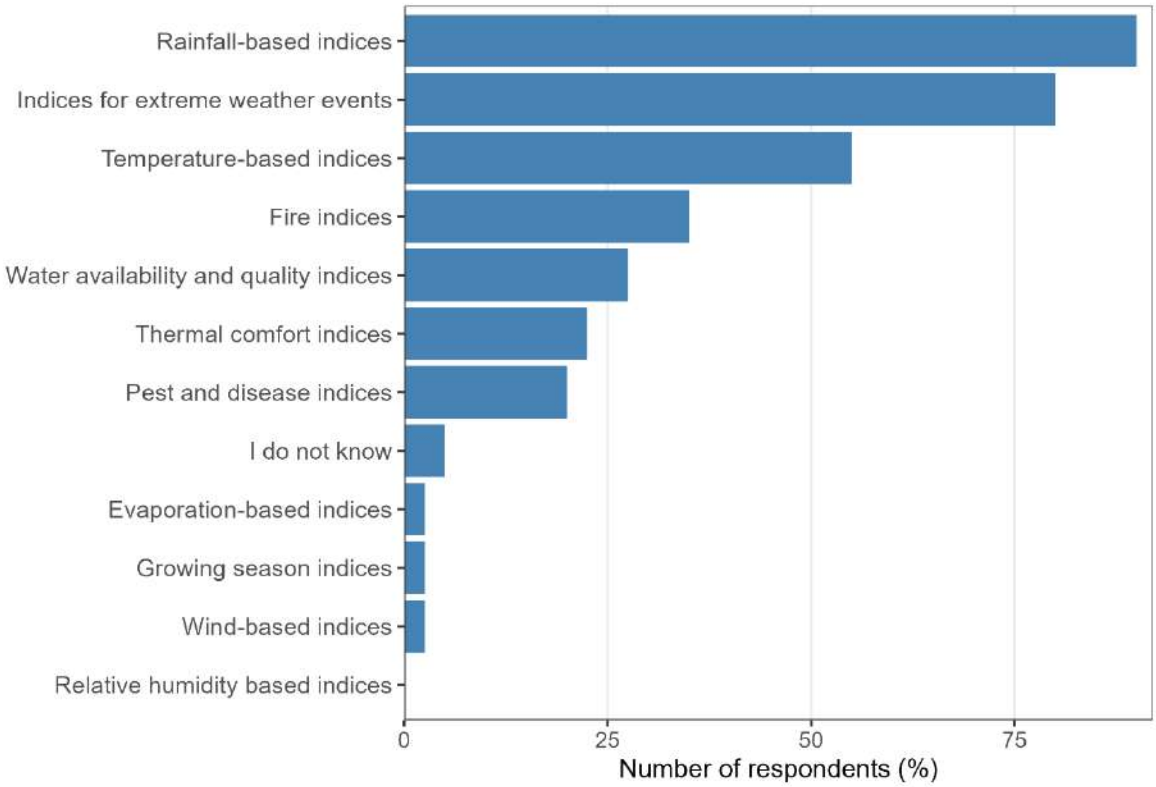

Figure 4.7: Types of weather and climate indices used to support activities within respondents' organisations/institutions/workplaces.

4.4.4 Constraints, decision drivers, and future weather and climate service (WCS) needs

To support effective decision-making in the agriculture and food security sector, it is important to understand the characteristics respondents value when selecting a WCS provider. Several determinants were identified, with the most frequently cited being that the provider is reputable and trustworthy (58%), that the data are freely available (45%), that support or training is offered (38%), that data costs are low (38%), and that the provider has a good understanding of the agricultural sector (35%; Figure 4.8). These findings highlight that uptake of WCSs is influenced not only by the availability of information but also by trust, affordability, and the perceived relevance of services to sector-specific needs. These considerations directly informed how the Weather Risk app was positioned and the emphasis placed on providing accessible, sector-relevant information.

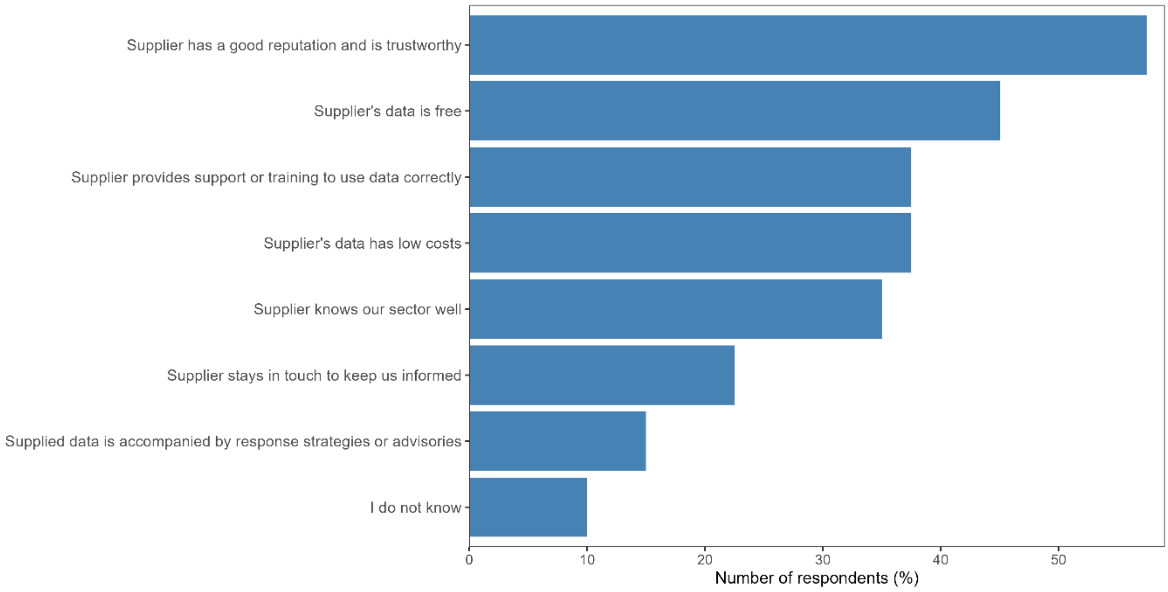

Figure 4.8: Key determinants influencing the choice of weather and climate service (WCS) providers or information sources amongst respondents' organisations/institutions/workplaces.

Respondents also identified several challenges associated with accessing and using existing WCSs (Figure 4.9). The most reported constraints included internet connectivity issues (33%) and energy supply disruptions (loadshedding; 28%; Figure 4.9). Other challenges related more directly to service design and usability, including limited availability of location-specific information (23%), concerns around data quality (18%), limited skills to use WCSs effectively (13%), high data costs (13%), and a lack of relevant or tailored services (10%; Figure 4.9). While infrastructure-related challenges such as connectivity and power supply are beyond the scope of app development, many of the remaining constraints were addressed through careful consideration of service design, data presentation, and user support during development of the Weather Risk app.

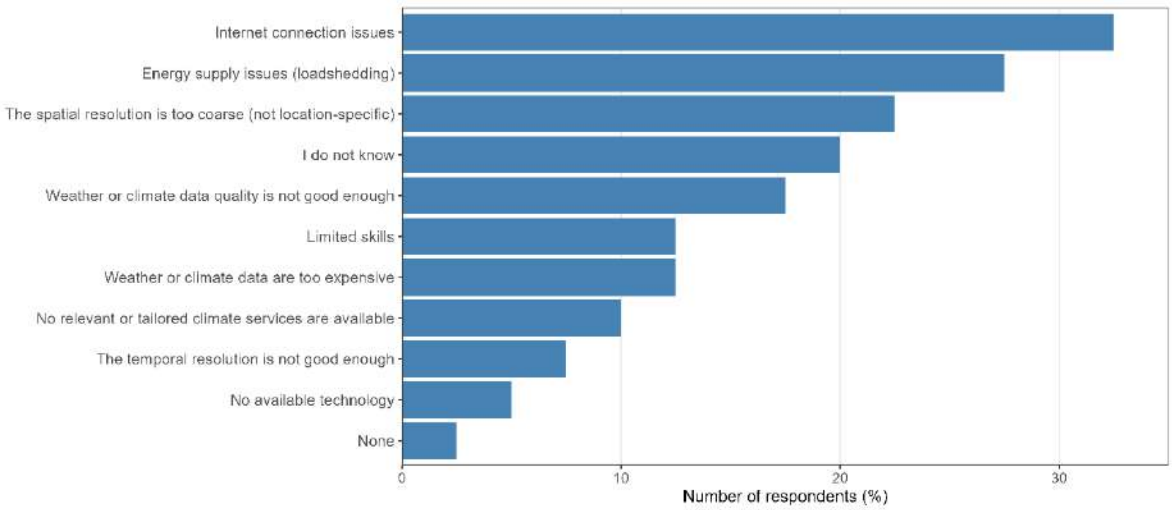

Figure 4.9: Constraints experienced by respondents' organisations/institutions/workplaces when accessing or using weather and climate services (WCSs).

To further inform development priorities, respondents were asked about their future WCS needs (Figure 4.10). The most frequently reported need was for access to historical weather and climate records (47%). Forward-looking services were also highlighted, including seasonal forecasts (24%), climate projections (21%), early warning systems (18%), and daily weather forecasts (18%; Figure 4.10). These results underscore the importance of combining historical context with short-term and anticipatory information. The Weather Risk app addresses these needs by providing short-term historical weather and water availability information, currently from 2023 onward, summarised at daily to monthly timescales, together with short- to medium-range forecast data to support near-term planning and decision-making. Longer-term historical datasets and climate projections are not included in the current version of the app, but the demand for such information identified here highlights potential areas for future expansion of the Weather Risk app.

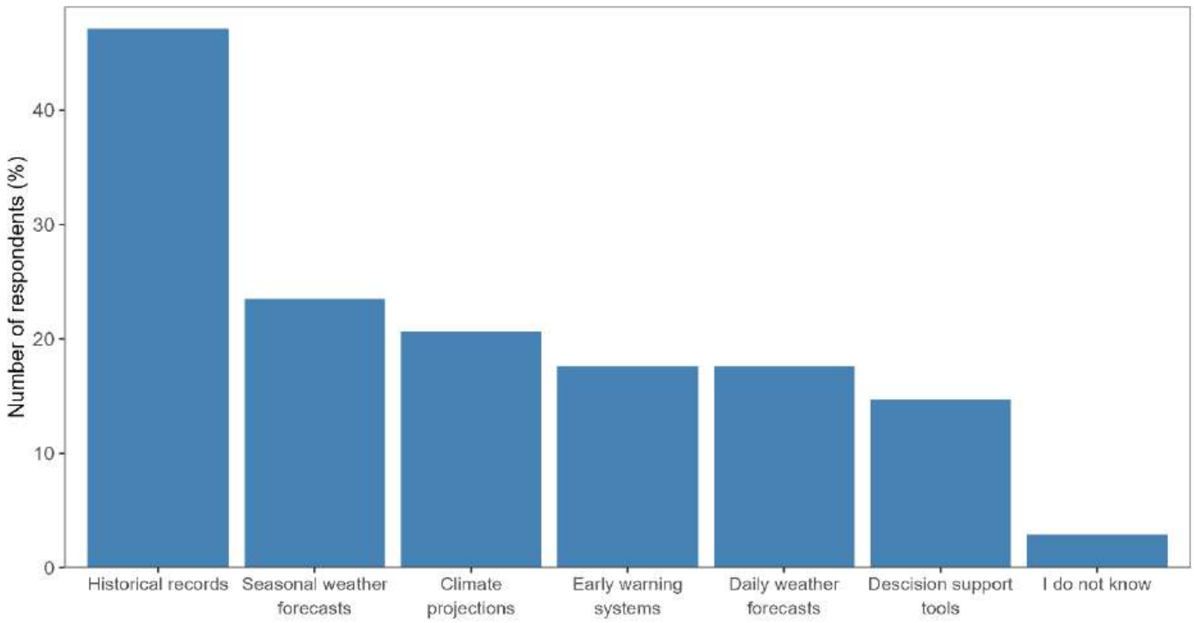

Figure 4.10: Types of weather and climate services (WCSs) the respondents' organisations/ institutions/workplaces would like to access in the future.

Overall, these findings indicate that the usability and uptake of WCSs depend on a combination of accessibility, relevance, trust, and user support. The design and implementation of the Weather Risk app reflect principles highlighted by Moeletsi and Tsubo (2024), including co-production, provision of context-specific and demand-driven information, timeliness, appropriate data formats, and services that enhance user experience and local applicability. Through the integration of stakeholder-informed design choices and iterative engagement during development, the Weather Risk app provides a platform that responds to identified needs within the agriculture and food security sector, while remaining adaptable to future enhancement as user requirements evolve.

4.5 Conclusions

This chapter demonstrated the importance of integrating stakeholder consultations and questionnaire-based evidence into the user-centred design of WCSs for the agriculture and food security sector. By combining insights from a national questionnaire with qualitative feedback from a regional stakeholder engagement, the chapter highlighted how perceptions of climatic risk, patterns of service use, and practical constraints directly shape information needs and expectations from digital climate services.

The findings underscore that effective WCSs must prioritise accessibility, trust, relevance, and usability, while responding to the sector's strong reliance on short-term, forward-looking information supported by recent historical context. The results also reinforced the value of presenting information through decision-relevant indices and providing interpretive guidance to support operational planning and risk management.

Overall, the stakeholder-informed evidence presented in this chapter provided a clear foundation for the design choices implemented in the Weather Risk app. By grounding development in co-production principles and sector-specific requirements, the app was positioned to deliver information that is both scientifically robust and practically applicable, supporting more informed and proactive decision-making within the agriculture and food security sector.

Chapter 5: Development of a web-based agrohydrometeorological indices app - the Weather Risk app

5.1 Introduction

This chapter documents the development of a web-based agrohydrometeorological indices platform, the Weather Risk app, and contributes directly to Objective 3 of the project, which focuses on the development and implementation of a web-based application to support agricultural decision-making. The Weather Risk app is accessible at www.weatherrisk.arc.agric.za. Here, the conceptual and technical development of the platform is discussed, including the selection of input weather and water datasets, the range of agrohydrometeorological indices included in the site, and the design and implementation of the web interface through which these data and indices are accessed. Although the platform is now operational and publicly available, it is important to note that the Weather Risk app is designed as a continuously evolving system, with ongoing refinements anticipated during at least the first year following its public release.

The development of the Weather Risk app responds to a recognised gap in existing WCSs, where large volumes of data are often available but are not consistently presented in a form that is easily accessible, interpretable, or directly applicable to agricultural decision-making at farm to district scales. While several platforms provide weather observations, forecasts, and climate information (as detailed under Section 2.2.3), these services often operate in isolation, require technical expertise to interpret, or lack explicit linkages to agricultural risk. The Weather Risk app seeks to contribute to addressing these gaps by integrating weather and water availability information within a single web-based platform, presenting this information through indices that are relevant to agricultural activities and risk management. The conceptualisation and development of the platform were informed not only by technical considerations but also by findings and insights presented earlier in the report, particularly those relating to user needs, priority climate risks, and the application of weather and climate indices discussed in Chapter 3.

In addition to development with awareness of user needs and operational contexts, design choices were guided by principles of clarity, consistency, and practical relevance. In this chapter, these considerations are reflected primarily through the types of indices included in the organisation of information within the site, and the overall functionality of the platform, rather than through a detailed discussion of stakeholder engagement or co-development processes, which are addressed elsewhere in the report. Notably, refinements currently underway include the implementation of feedback received during internal feedback workshops held with ARC staff during the later stages of the project, the outcomes of which are presented in Chapter 6. Further adjustments and enhancements are expected as the site is used in practice, and additional feedback is received from external users following publicisation.

Considering this chapter, it first outlines the general design approach adopted for the Weather Risk app, followed by a description of the weather datasets and weather-based indices included in the platform, with brief methodological notes where relevant. It then presents the water-related datasets and indices incorporated into the site, before describing the overall design and development of the platform, including potential future enhancements identified during the project. The chapter also documents the development of the Weather Risk app user guide and associated GitHub repository, produced to support effective and consistent use of the platform. It also outlines ongoing activities to publicise the Weather Risk app. The chapter concludes with a summary of key development outcomes, recognising that the Weather Risk app will continue to be refined beyond the formal project timeframe as part of an ongoing process of improvement, user engagement, and institutional support.

5.2 User-centric design of the app

The design and development of the Weather Risk app were guided by a user-centric approach informed by stakeholder engagement activities presented in Chapter 4. Initial consultations were used to identify priority information needs, preferred timescales, and key usability considerations relevant to agricultural decision-making in South Africa. These insights directly informed the selection of weather and water indices, the emphasis on short-term and near-real-time information, and the overall structure and layout of the app interface.

In addition to this early input, the user-centric approach was maintained throughout the development process through targeted feedback workshops focused specifically on the Weather Risk app itself. These engagements provided practical guidance on site functionality and presentation, including suggestions related to colour schemes used for indices, the wording and naming of indices, the inclusion of points of interest to enable more location-specific interpretation, and other interface refinements aimed at improving clarity and usability. The outcomes of these feedback workshops and the resulting site enhancements are presented in detail in Chapter 6.

By incorporating stakeholder input both at the conceptual design stage and during subsequent testing and refinement phases, the Weather Risk app was intentionally developed to prioritise interpretability, accessibility, and practical relevance. This iterative, user-centred process was intended to support improved uptake of the platform and to strengthen its value as a decision-support tool for weather-informed planning and risk management across the agricultural sector.

5.3 Input weather data and weather indices for the Weather Risk app

5.3.1 Weather data

The weather data incorporated into the Weather Risk app are derived from in-house ARC data records and include both observed weather station measurements and short- to medium-range forecast products.

Observed meteorological data are sourced from the ARC weather station network, which comprises approximately 600 stations distributed across South Africa (Figure 5.1). At an hourly temporal resolution, each station measures air temperature (°C), rainfall (mm), relative humidity (%), solar radiation ($W.m^{-2}$), wind speed ($m.s^{-1}$), and wind direction (°; Moeletsi et al., 2022). In addition to these measured variables, several derived metrics are calculated, including PET, using the Penman-Monteith method, and cold and heat units (Moeletsi et al., 2022). All measured and derived variables were considered for inclusion in the Weather Risk app, with the intention that the full suite will ultimately be made available, as discussed in Section 5.3.2.

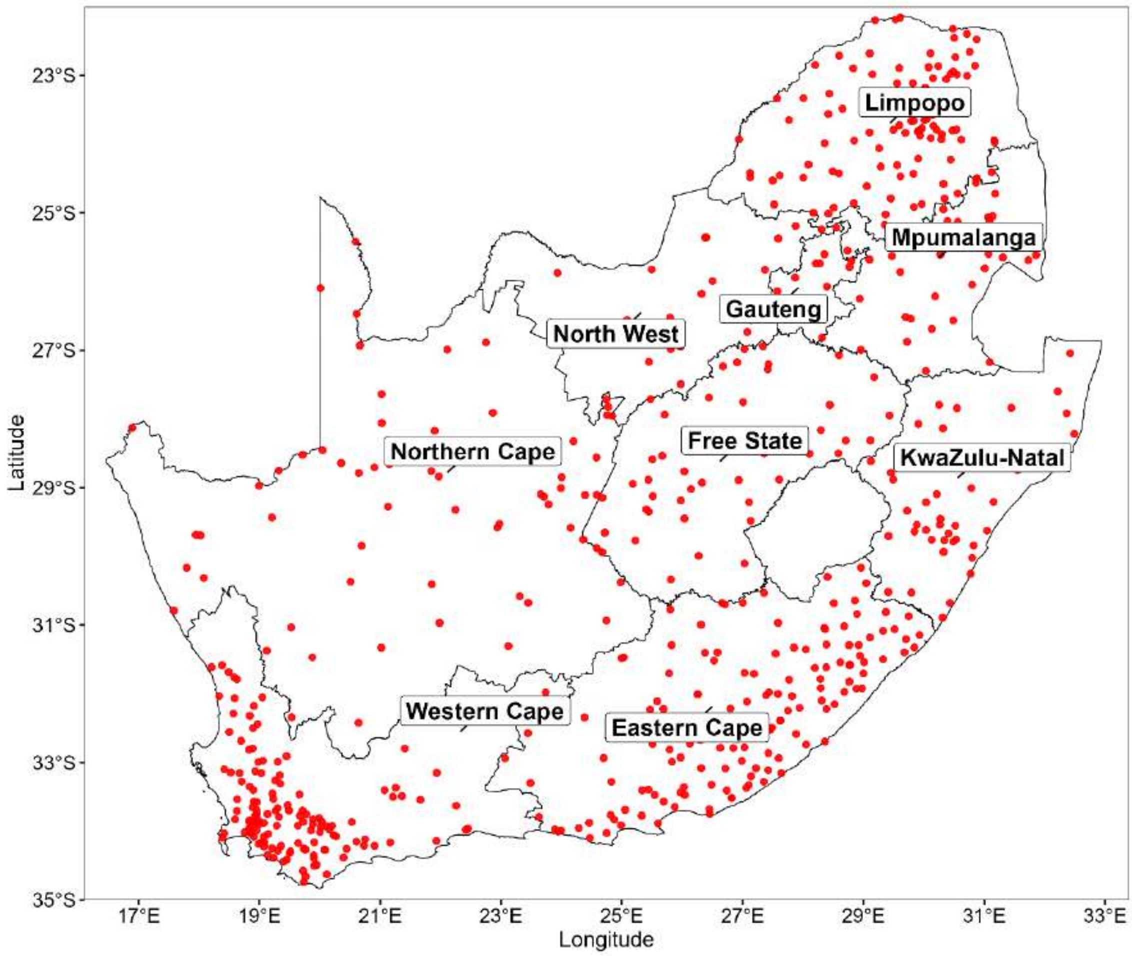

Figure 5.1: Spatial distribution of active Agricultural Research Council (ARC) weather stations across South Africa as of December 2025.

For operational use within the Weather Risk app, observed hourly station data are available with a 24-hour reporting delay. Hourly observations are then aggregated to daily values and subsequently interpolated daily to gridded GeoTIFF surfaces (Figure 5.2; Malherbe et al., 2025) . At present, the Weather Risk app provides gridded observational data from January 2023 onwards for all variables, with new observation daily surfaces available for each index with a two-day delay.

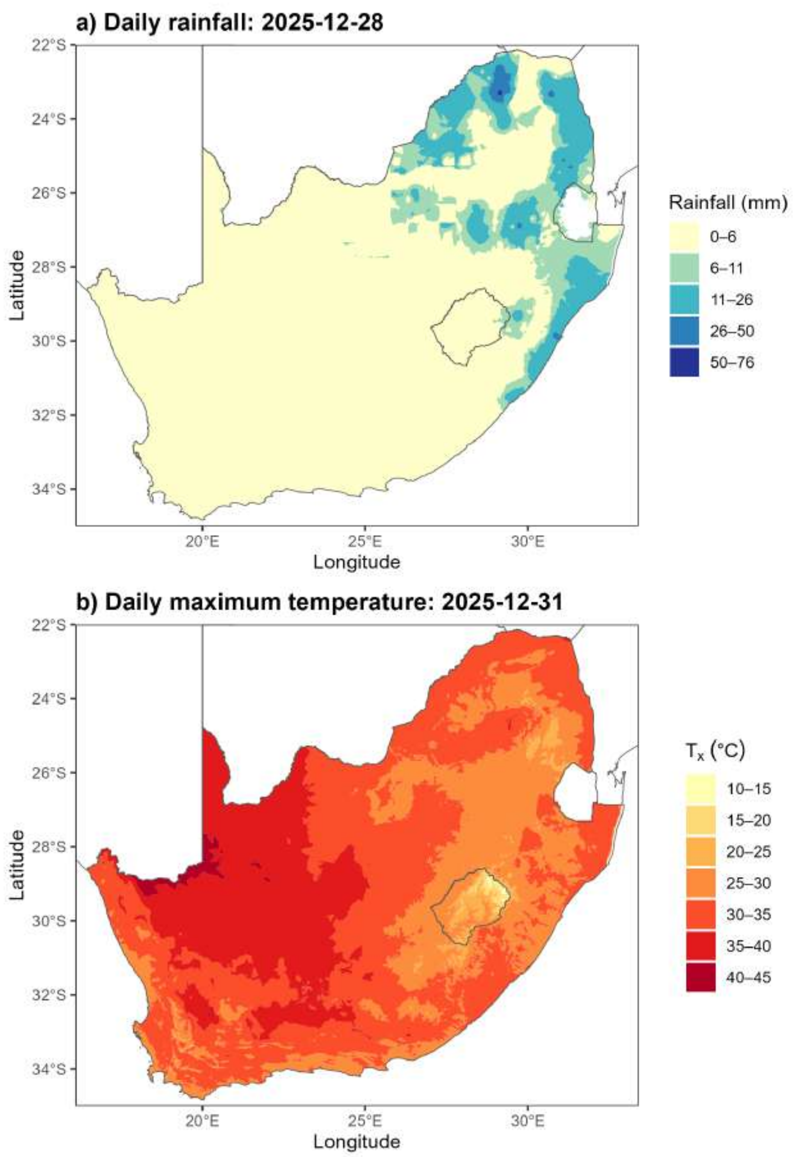

Figure 5.2: Example maps of interpolated weather station data for selected variables over South Africa.

For the spatial interpolation of station data, an inverse distance weighting approach is applied. To enhance the realism and spatial coherence of the interpolated outputs, high-resolution gridded datasets are incorporated as supporting spatial surfaces. For rainfall, both the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) long-term average climatology and the daily CHIRPS rainfall surfaces are used alongside ARC station observations during the daily interpolation process (Funk et al., 2015). For all other meteorological variables, long-term average ERA5-Land surfaces are utilised as spatial reference fields (Muñoz-Sabater et al., 2021). The inclusion of these gridded datasets enables realistic spatial variability to be represented at a 1 km x 1 km resolution. The resulting interpolated surfaces form the basis for the computation of the weather and climate indices described in Section 5.3.2.

Forecast data incorporated into the Weather Risk app are generated from a daily operational run of the Weather Research and Forecasting (WRF) model, version 4.0, using the Advanced Research WRF (ARW) dynamical core (Skamarock et al., 2021). Each day at 07:30 South African

Standard Time (SAST), the forecasting workflow is initiated by downloading initial and boundary condition data from the National Centers for Environmental Prediction (NCEP) Global Forecast System (GFS; NCEI, 2025). The GFS data have a horizontal resolution of approximately 28 km × 28 km and extend to 16 days ahead, with hourly output available for the first 120 hours and a 3-hourly temporal resolution for days 5-16 (NCEI, 2025).

Using the WRF model, a daily forecast is produced for the southern African domain (approximately 20-38°S and 11-38°E; Figure 5.3). The model is configured at a horizontal resolution of 12 km x 12 km, covering 212 x 157 grid points and 34 vertical levels extending from the surface to 50 hPa. Notably, in the future, with additional resources, we aim to improve the spatial resolution of the forecast output. Forecasts are generated at an hourly temporal resolution for lead times of 1 to 168 hours (i.e., seven days) ahead of 00:00 Coordinated Universal Time (UTC). An adaptive time step is employed, with a minimum time step of 1 second and a maximum of 180 seconds.

Figure 5.3: Spatial extent of the Weather Research and Forecasting (WRF) model forecast domain covering southern Africa.

The physical parameterization schemes selected for the model configuration include: the WRF single-moment 6-class microphysics scheme (Hong & Lim, 2006); the Dudhia shortwave radiation scheme and the Rapid Radiative Transfer Model longwave radiation scheme (Dudhia, 1989; Mlawer et al., 1997); the Betts-Miller-Janjic cumulus parameterisation (Betts & Miller, 1986; Janjić, 1994); the Yonsei University planetary boundary layer scheme (Noh et al., 2003); the revised MM5 surface layer scheme (Jiménez et al., 2012); and the Noah land surface model (Ek et al., 2003). These parameterization choices were informed by the characteristics of the simulation domain, findings from previous modelling studies over southern Africa (e.g., Crétat et al., 2011; Crétat & Pohl, 2012; Ratnam et al., 2012; Ratna et al., 2013; Bopape et al., 2021), and targeted weather event simulations conducted by the project team (e.g., snow event simulation presented in publication listed under Appendix A2.2).

The completed WRF forecast output contains a wide range of meteorological variables at both the surface and selected pressure levels. However, only variables directly relevant to agrometeorological decision-making are extracted for further processing and dissemination through the Weather Risk app. At the surface, these include rainfall, air temperature, relative humidity, solar radiation, surface pressure, and sea-level pressure measured at 2m, with near-surface u- and v-wind components at 10m. PET is subsequently computed using the Penman-Monteith approach (Allen et al., 2006). Soil moisture and soil temperature variables are also extracted. At selected pressure levels (850, 500, and 200 hPa), geopotential height, temperature, relative humidity, and u- and v-wind components are retained for diagnostic and research purposes.

Although formal statistical validation of the forecast output is ongoing, routine visual inspection of forecast fields currently serves as an interim quality-control measure. For operational use within the Weather Risk app, only surface variables are included after conversion to daily SAST outputs (Figure 5.4). The inclusion of the full suite of forecast variables is planned for future implementation, as discussed in Section 5.3.2. Notably, in the Weather Risk app, all forecast indices are updated by 13:00 SAST for the current day, with data presented in all instances for seven days ahead.

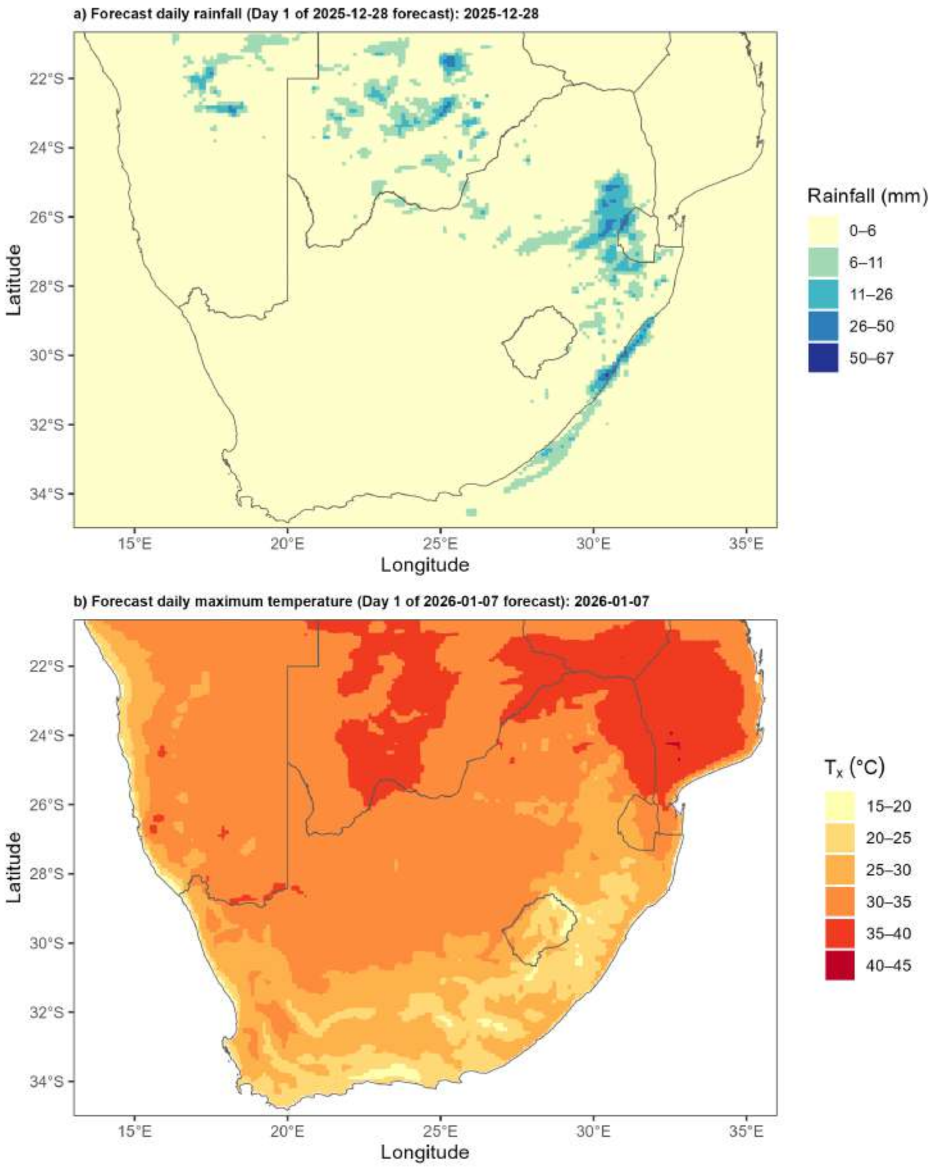

Figure 5.4: Example maps illustrating forecasted model output for selected variables over South Africa.

5.3.2 Weather indices

The Weather Risk app includes a wide range of weather indices that have either been implemented or are planned to be implemented. These indices are grouped under tabs (discussed further under Section 5.5) of rainfall, low temperature, high temperature, thermal comfort, fire, PET, and wind indices (Table 5.1). Although not currently planned, further indices, such as cold and heat units, and solar radiation indices, may be incorporated over time once the indices in Table 5.1 are complete. These may include indicators suggested through user engagement, indices identified as relevant through ongoing research, or new products developed within the ARC Agrometeorology Division. Notably, as knowledge sharing, code for many of the weather indices is available on the GitHub repository via https://github.com/climindex/hydroclimsa/tree/main/Hydromet_indices.

Table 5.1: Details of the weather indices included in the Weather Risk app.

Index (status of inclusion in the app)	Description as per Weather Risk app	Data used for the index
	Low temperature indices	
Frost (included in the app)	This index represents the occurrence of frost, classified according to severity: Light (below 2 °C), Moderate (below 0 °C), and Severe (below -2 °C). Additionally, for the forecast, the number of hours per day spent in each frost category is provided, giving farmers a clearer picture of how long these conditions may persist. For crop farmers, it helps monitor the risk of frost damage to sensitive crops and guide decisions on frost protection measures. For livestock farmers, it provides insights into potential cold stress on animals, helping to inform strategies for sheltering livestock during frost events.	Observed daily minimum temperature and seven-day forecasted minimum temperature data
Daily minimum temperature (included in the app)	This index represents the absolute lowest daily temperature measured in °C. For crop farmers, it helps assess the risk of frost damage or cold stress to crops, especially sensitive ones. For livestock farmers, it provides information on potential cold stress risks for animals and can guide decisions regarding shelter or feeding strategies during extreme cold events.	Observed daily minimum temperature and seven-day forecasted minimum temperature data

Index (status of inclusion in the app)	Description as per Weather Risk app	Data used for the index
Lowest daily temperature (last 10 days) (included in the app)	This index represents the coldest daily minimum temperature, measured in °C, over the last 10 days. For crop farmers, it helps assess the risk of frost damage or cold stress on crops, particularly for sensitive varieties. For livestock farmers, it provides insights into the potential for cold stress on animals, guiding decisions on shelter and additional care during extreme cold conditions.	Observed daily minimum temperature
High temperature indices		
Daily maximum temperature (included in the app)	This index represents the absolute highest daily temperature measured in °C. For crop farmers, it helps assess the risk of heat stress on crops, particularly during critical growth stages. For livestock farmers, it provides insights into potential heat stress risks for animals, helping to guide decisions on water availability, shade, and other cooling measures during extreme heat events.	Observed daily maximum temperature and seven-day forecasted maximum temperature data
Heat stress days (last 10 days) (included in the app)	This index represents the number of days with a daily maximum temperature above 30 °C over the last 10 days. For crop farmers, it helps assess the risk of heat stress on crops, which can impact growth and yield. For livestock farmers, it provides insights into the potential for heat stress on animals, guiding decisions on managing animal welfare, including providing shade, water, and ventilation during hot conditions.	Observed daily maximum temperature

Index (status of inclusion in the app)	Description as per Weather Risk app	Data used for the index
Highest daily temperature (last 10 days) (included in the app)	This index represents the hottest daily maximum temperature, measured in °C, over the last 10 days. For crop farmers, it helps assess the risk of heat stress on crops, particularly during sensitive growth stages. For livestock farmers, it provides insights into the potential for heat stress on animals, aiding in decisions related to animal welfare management, such as providing extra water, shade, or shelter during extreme heat events.	Observed daily maximum temperature
Thermal comfort indices		
Heat index (HI) (included in the app)	This index uses air temperature and relative humidity to estimate heat stress risk in humans. It classifies conditions into levels of caution, extreme caution, danger, and extreme danger. The index helps farmers recognise when outdoor work may become hazardous, supporting decisions to adjust work hours and ensure adequate shade, water, and rest during hot conditions.	Observed daily and seven-day forecasted HI data derived from variables listed under description
Temperature-humidity index (THI) cattle (included in the app)	This index, calculated using air temperature and relative humidity, assesses heat stress risk in cattle, categorising conditions into moderate, high, and extreme heat stress. It helps farmers anticipate heat stress, guiding decisions on providing shade, water, and other cooling measures to protect goats during hot conditions.	Observed daily and seven-day forecasted THI data derived from variables listed under description
THI goats (included in the app)	This index, calculated using air temperature and relative humidity, assesses heat stress risk in goats, categorising conditions into moderate, high, and extreme heat stress. It helps farmers anticipate heat stress, guiding decisions on providing shade, water, and other cooling measures to protect cattle during hot conditions.	Observed daily and seven-day forecasted HI index data derived from variables listed under description

Index (status of inclusion in the app)	Description as per Weather Risk app	Data used for the index
THI sheep (included in the app)	This index, calculated using air temperature and relative humidity, assesses heat stress risk in sheep, categorising conditions into moderate, high, and extreme heat stress. It helps farmers anticipate heat stress, guiding decisions on providing shade, water, and other cooling measures to protect sheep during hot conditions.	Observed daily and seven-day forecasted thermal heat index data derived from variables listed under description
THI poultry (included in the app)	This index, calculated using air temperature and relative humidity, assesses heat stress risk in poultry, categorising conditions into moderate, high, and extreme heat stress. It helps farmers anticipate heat stress, guiding decisions on providing shade, water, and other cooling measures to protect poultry during hot conditions.	Observed daily and seven-day forecasted thermal heat index data derived from variables listed under description
THI pigs (included in the app)	This index, calculated using air temperature and relative humidity, assesses heat stress risk in pigs, categorising conditions into moderate, high, and extreme heat stress. It helps farmers anticipate heat stress, guiding decisions on providing shade, water, and other cooling measures to protect pigs during hot conditions.	Observed daily and seven-day forecasted thermal heat index data derived from variables listed under description
	Fire indices	
Fire danger index (included in the app)	This index, calculated as the Lowveld Fire Danger Index using temperature, relative humidity, wind speed, and rainfall, is used to assess fire risk levels, ranging from safe to extremely dangerous. It provides farmers with valuable information for fire preparedness, helping to guide decisions on fire prevention measures, land management, and the protection of crops, infrastructure, and livestock during high-risk periods.	Observed daily and seven-day forecasted fire danger index data derived from variables listed under description
	Rainfall indices	

Index (status of inclusion in the app)	Description as per Weather Risk app	Data used for the index
Daily rainfall (included in the app)	This index represents the total rainfall (in mm) recorded over a single day, offering farmers a snapshot of daily moisture inputs. For crop farmers, it helps assess immediate soil moisture availability, whether conditions are too wet—posing risks such as waterlogging and erosion—or too dry, which may hinder planting or crop establishment. It also aids in identifying heavy rainfall events or dry spells that could impact fieldwork and crop growth. For livestock farmers, it provides insights into water availability in grazing areas and helps evaluate potential impacts on pasture condition, livestock movement, and access to water sources, particularly during periods of extreme rainfall or dryness.	Observed daily rainfall and seven-day forecasted rainfall data
Number of rain days (last 30 days) (included in the app)	This index represents the number of days with rainfall exceeding 1 mm over the past 30 days, offering farmers a clearer picture of how frequently rain has fallen. For crop farmers, this information can assist in evaluating soil moisture conditions, planning fieldwork, and determining the effectiveness of recent rainfall for supporting crop growth. For livestock farmers, it provides insights into the availability of water for grazing areas, the condition of pastures, and the potential for muddy or waterlogged conditions that may affect livestock movement or health.	Observed daily rainfall data

Index (status of inclusion in the app)	Description as per Weather Risk app	Data used for the index
Days since last rain (up to 60 days) (included in the app)	This index represents the number of days since the last rainfall within the past 60 days, helping farmers track the duration of dry conditions. For crop farmers, this information is useful for assessing soil moisture levels, scheduling irrigation, and monitoring drought risk. For livestock farmers, it provides insights into water availability for grazing areas, the condition of pastures, and the potential need to adjust livestock management strategies during prolonged dry periods.	Observed daily rainfall data
Maximum daily rainfall (last 30 days) (included in the app)	This index represents the maximum daily rainfall (in mm) recorded over the past 30 days, helping farmers identify the most intense rainfall event during this period. For crop farmers, this information is useful for assessing potential impacts such as soil erosion, waterlogging, or damage to crops and infrastructure, and for planning drainage or recovery measures. For livestock farmers, it provides insights into potential flooding of grazing areas, access issues to water sources, or the need to move animals to higher ground during heavy rainfall events.	Observed daily rainfall data
Total rainfall (last 10 and 30 days) (included in the app)	This index represents the total rainfall (in mm) accumulated over the past 10 and 30 days, providing farmers with insights into recent moisture availability. For crop farmers, it can help inform decisions such as planting schedules, irrigation planning, and assessing soil conditions for fieldwork or crop growth. For livestock farmers, it offers valuable information about water availability in grazing areas, the condition of pastures, and potential risks of waterlogging or reduced accessibility to grazing lands.	Observed daily rainfall data
Potential evapotranspiration (PET) indices		

Index (status of inclusion in the app)	Description as per Weather Risk app	Data used for the index
Daily PET (included in the app)	This index represents the daily potential evapotranspiration, calculated using the Penman-Monteith equation. It reflects the atmospheric demand for moisture on a given day and indicates how much water could be evaporated and transpired under optimal conditions. For crop farmers, it helps gauge short-term water demand and supports irrigation planning during hot or dry periods. For livestock farmers, it provides insight into daily pasture water needs and potential heat or drought stress, informing decisions on water provision and grazing management.	Observed daily and seven-day forecasted PET data derived from variables used to calculate the Penman-Monteith equation
Total PET (last 10 and 30 days) (included in the app)	This index represents the total potential evapotranspiration value for the last 10 and 30 days, calculated using the Penman-Monteith equation. It measures the maximum amount of water that could be evaporated and transpired from a land surface to the atmosphere under optimal conditions. For crop farmers, it helps assess water demand for crops, guiding irrigation planning and water management strategies, particularly during dry and hot conditions when water resources may be limited. For livestock farmers, it provides insights into pasture water requirements and the potential for heat stress, helping to inform strategies for ensuring water availability, managing grazing areas, and safeguarding animal welfare during periods of excessive heat or drought.	Observed daily potential evaporation data
	Wind indices	

Index (status of inclusion in the app)	Description as per Weather Risk app	Data used for the index
Damaging winds (last 10 days) (still to be included in the app)	This index represents the total number of days in the last 10 days on which wind speeds exceeded 17 $m.s^{-1}$ for at least one hour, classified as gale-force or stronger winds according to the Beaufort scale. At this level, winds can cause crop lodging, increased soil erosion, and challenges in applying fertilisers or pesticides due to drift, helping crop farmers identify risks and implement preventative measures to minimise losses. For livestock farmers, it signals periods of high winds that may affect grazing conditions, animal welfare, and the stability of shelters, enabling timely actions to protect resources and infrastructure.	Observed daily maximum wind speed data
Damaging winds (forecast) (still to be included in the app)	This index represents the total number of hours forecasted in a day when wind speeds may exceed 17 $m.s^{-1}$, classified as gale-force or stronger winds according to the Beaufort scale. At this level, winds can cause crop lodging, increase soil erosion, and present challenges in applying fertilisers or pesticides due to drift, helping crop farmers identify risks and implement preventative measures to minimise losses. For livestock farmers, it signals periods of high winds that may affect grazing conditions, animal welfare, and the stability of shelters, enabling timely actions to protect resources and infrastructure.	Seven-day forecasts of hourly wind speed

The Weather Risk app includes five rainfall indices (Table 5.1; Figures 5.5-5.6) designed to characterise recent and near-term rainfall conditions relevant to agricultural activities. These indices include: 1) the observed and forecast daily rainfall (in mm), 2) the total observed rainfall accumulated over the last 10 and 30 days (in mm), 3) the observed number of rain days over the last 30 days (in days) with a rain day defined as a day with above 1 mm, 4) the observed number of days since rainfall (above 1 mm) last occurred within the past 60 days (in days), and 5) the observed maximum daily rainfall over the last 30 days (in mm; Table 5.1; Figure 5.5-5.6).

Descriptions of each index are provided in Table 5.1. Apart from the daily rainfall forecast presented for seven days ahead, all rainfall indices are computed using daily rainfall data.

Each rainfall index was selected based on its direct agricultural relevance and its ability to support both short-term operational decisions and broader planning for crop and livestock systems. Daily rainfall provides immediate information for irrigation scheduling, planting and harvesting activities, grazing management, and assessment of surface wetness and field access. Total rainfall accumulated over the last 10 and 30 days reflects short-term moisture availability and overall wetness, supporting decisions related to crop establishment, supplemental irrigation, pasture growth potential, and grazing pressure. The number of rain days over the last 30 days captures rainfall frequency, which is important for understanding soil moisture replenishment, pasture response, and crop growth conditions. The number of days since the last occurrence serves as an indicator of developing dry spells, informing early responses such as irrigation planning, grazing rotation, feed supplementation, or closer monitoring of water supplies. Finally, maximum daily rainfall over the last 30 days highlights the occurrence of intense rainfall events, which are relevant for identifying risks associated with runoff, erosion, waterlogging, infrastructure damage, and restricted livestock movement. Collectively, these indices provide complementary information on rainfall amount, frequency, persistence, and intensity, supporting weather-informed agricultural planning and risk management.

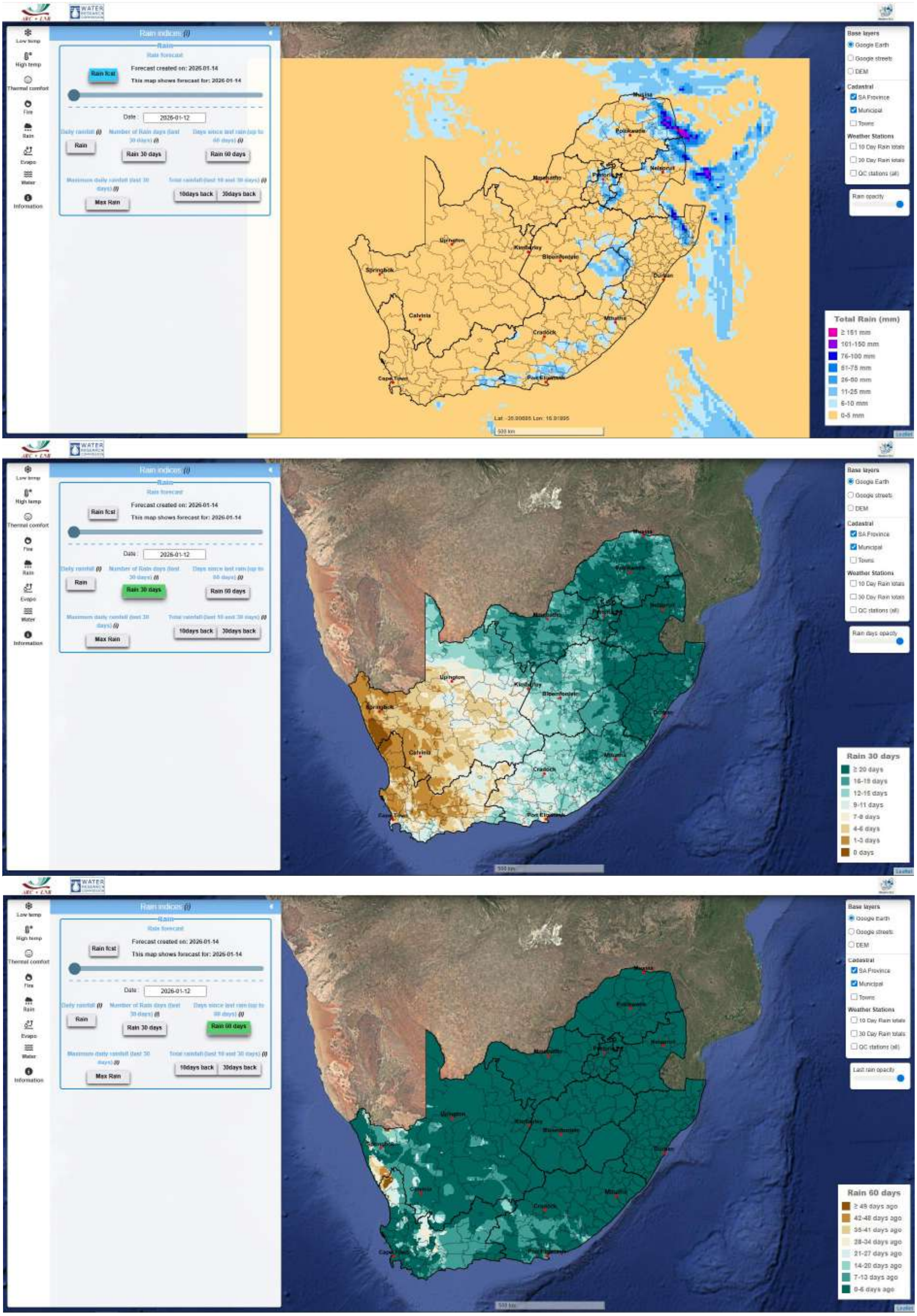

Figure 5.5: Day one forecast for 14 January 2026 of daily rainfall (top), along with the number of rain days (last 30 days; middle) and the days since last rain (up to 60 days; bottom) for 12 January 2026, as displayed in the Weather Risk app.

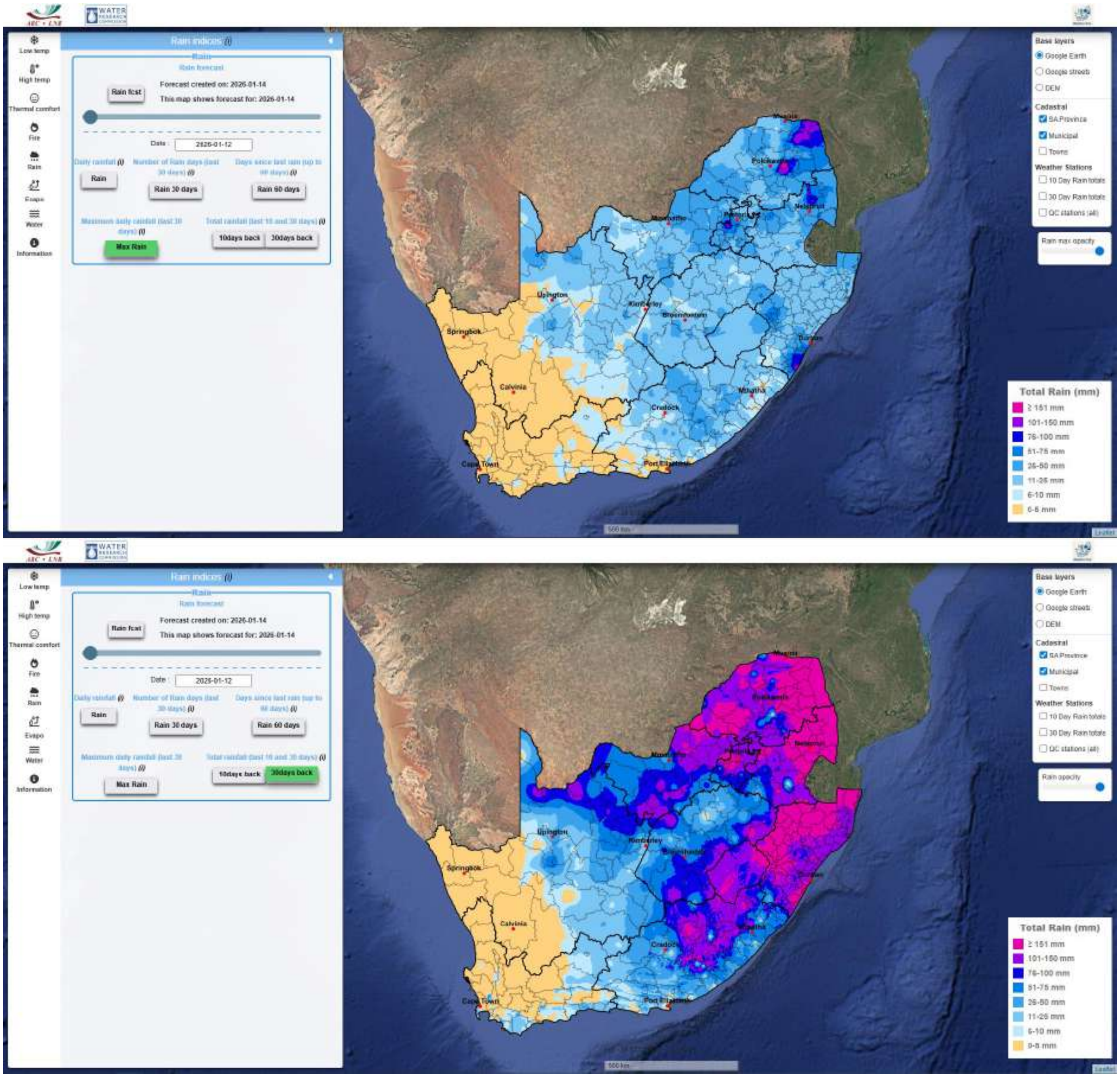

Figure 5.6: Maximum daily rainfall (last 30 days; top) and total rainfall (last 30 days; bottom) for 12 January 2026, as displayed in the Weather Risk app.

The Weather Risk app includes three high temperature indices (Table 5.1; Figures 5.7) designed to characterise recent and near-term exposure to elevated daytime temperatures relevant to agricultural activities. These indices include: 1) observed and forecast daily maximum temperature (in °C), 2) the observed number of heat stress days during the last 10 days, where a heat stress day is defined as a day with a maximum temperature exceeding 30 °C (in days), and 3) the observed highest daily maximum temperature recorded over the last 10 days (in °C; Table 5.1; Figure 5.7). Descriptions of each index are provided in Table 5.1. Apart from the daily maximum temperature forecast presented for seven days ahead, all high temperature indices are computed using observed daily maximum temperature GeoTIFF data surfaces.

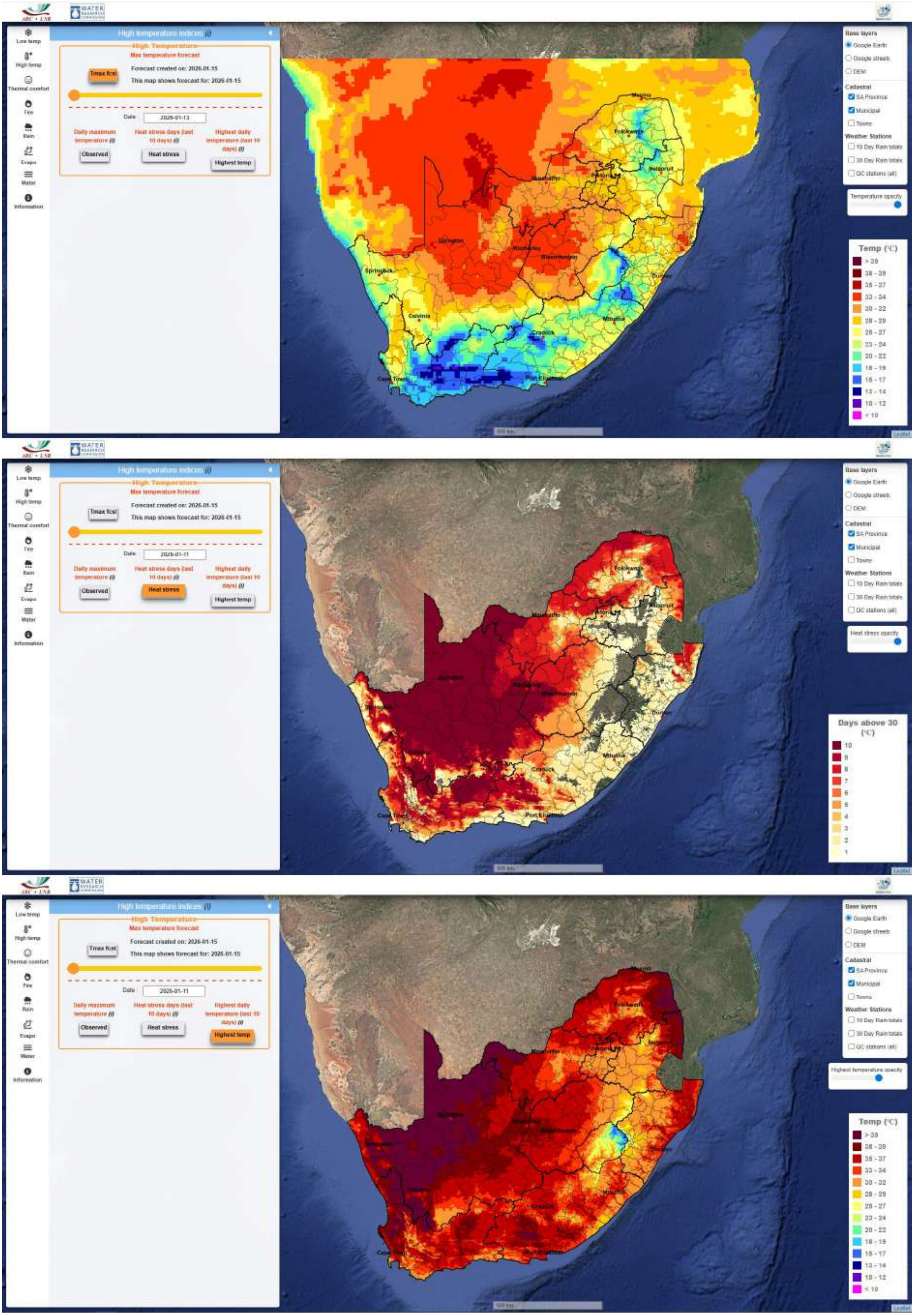

Figure 5.7: Day one of the daily maximum temperature forecast for 15 January 2026 (top), along with heat stress days (last 10 days; middle) and highest daily temperature (last 10 days; bottom) for 11 January 2026, as displayed in the Weather Risk app.

Each high temperature index was selected based on its relevance for identifying heat-related risks to crops and livestock and for supporting short-term management decisions. Daily maximum temperature provides information on current and forecast heat exposure, supporting the monitoring of heat stress risks during sensitive crop growth stages such as flowering or grain filling, as well as informing livestock management decisions related to shade provision, water availability, and grazing timing. The number of heat stress days during the last 10 days captures repeated exposure to elevated temperatures, which can place cumulative stress on crops and animals even when individual days are not extreme; this index is particularly useful for identifying prolonged hot spells that may reduce crop productivity or contribute to heat-related stress, reduced feed intake, or lowered performance in livestock. The highest daily maximum temperature over the last 10 days highlights peak heat exposure in the recent past, supporting assessments of potential heat damage to crops and evaluation of the effectiveness of heat-mitigation measures for livestock, such as shaded areas, watering points, and changes in daily management practices. Collectively, these indices provide complementary information on the intensity and persistence of high daytime temperatures, supporting heat-risk awareness and adaptive decision-making in agricultural systems.

The Weather Risk app includes three cold temperature indices (Table 5.1; Figure 5.8) designed to characterise recent and near-term exposure to low temperatures relevant to agricultural activities. These indices include: 1) observed and forecast daily minimum temperature (in °C), 2) observed and forecast frost occurrence classified as light, moderate, and severe frost, where observed and forecast outputs represent the spatial extent of each frost category and the forecast additionally provides the expected number of frost hours per day, and 3) the observed coldest daily minimum temperature recorded over the last 10 days (in °C; Table 5.1; Figure 5.8). Descriptions of each index are provided in Table 5.1. Apart from the daily minimum temperature and frost forecasts presented for seven days ahead, all cold temperature indices are computed using observed daily minimum temperature GeoTIFF data surfaces.

Each cold temperature index was selected based on its relevance for identifying frost and cold-stress risks to crops and livestock and for supporting timely management decisions. Daily minimum temperature is a key indicator of cold exposure and frost risk, supporting assessments of crop vulnerability during early growth or flowering stages and informing cold-weather planning for livestock; for example, forecast minimum temperatures below 2 °C may prompt protective actions such as delaying planting, covering seedlings, or providing additional feed and shelter for young or vulnerable animals. Frost occurrence, classified into light, moderate, and severe categories, provides critical guidance for managing frost-related risks by indicating both the expected severity and spatial extent of frost events, with forecast frost hours offering additional insight into exposure duration; this information supports decisions such as implementing frost protection measures in crops or relocating livestock to sheltered areas during prolonged frost conditions. The coldest daily minimum temperature over the last 10 days highlights recent extreme cold exposure, supporting post-event assessment of potential frost damage in crops and evaluation of cold stress impacts on livestock, and informing follow-up actions such as crop inspections, increased feeding, or closer animal health monitoring. Collectively, these indices provide complementary information on the intensity, duration, and severity of cold conditions, supporting proactive management of cold-related agricultural risks.

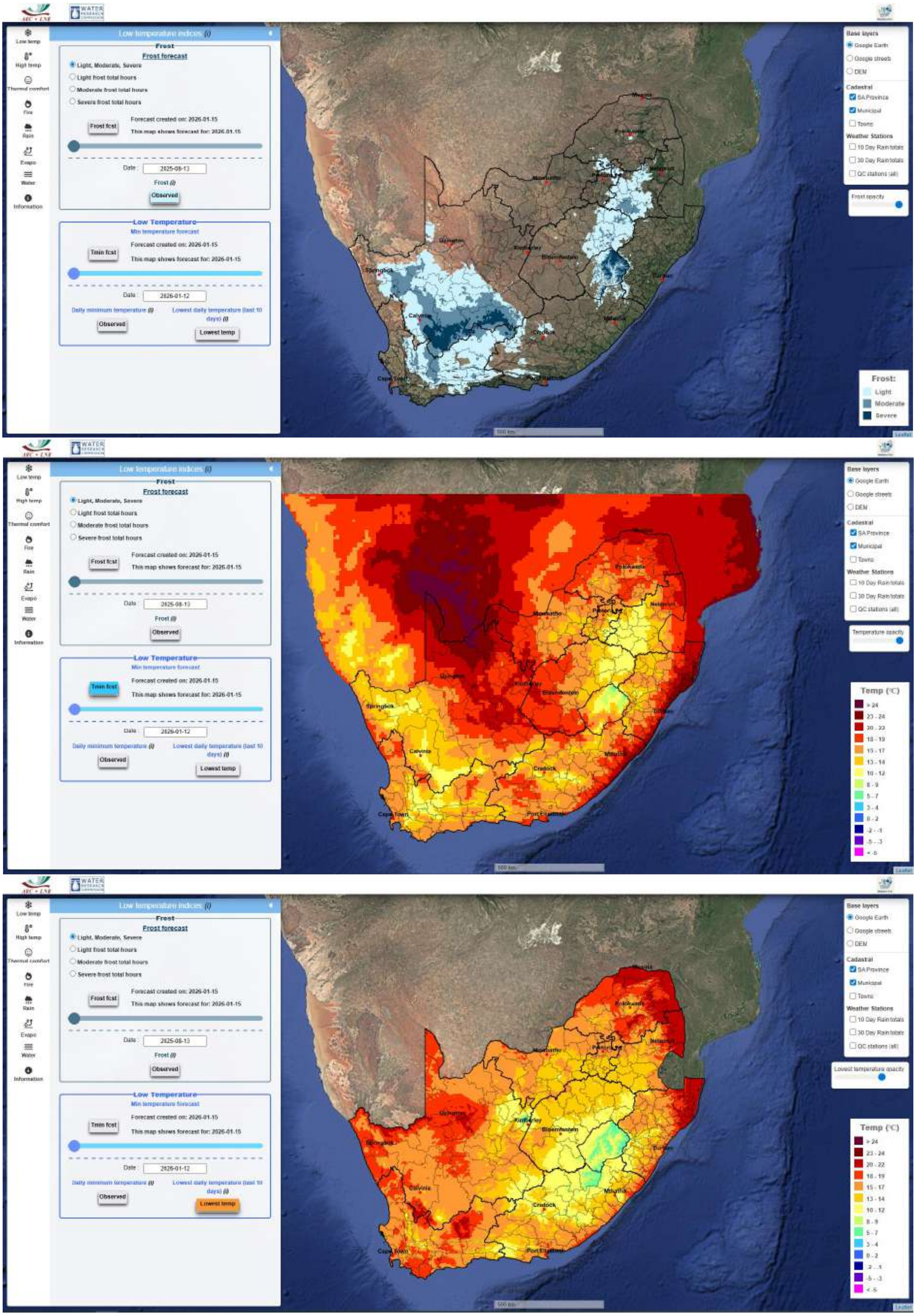

Figure 5.8: Observed frost for 13 August 2025 (top), along with day one of the daily minimum temperature forecast for 15 January 2026 (middle) and lowest daily temperature (last 10 days; bottom) for 12 January 2026, as displayed in the Weather Risk app.

The Weather Risk app includes two thermal comfort indices (Table 5.1; Figure 5.9) designed to characterise heat stress risk conditions relevant to both human activities and livestock production systems. These indices include: 1) the Heat Index (HI), which combines air temperature and relative humidity to indicate heat stress risk levels for humans, categorised as caution, extreme caution, danger, and extreme danger, and 2) the THI, which is also based on air temperature and relative humidity and is used to assess heat stress risk for livestock (Table 5.1; Figure 5.9). Observed THI outputs are delineated into categories of moderate, high, and extreme heat stress for different livestock types, including goats, cattle, sheep, poultry, and pigs, while the forecast THI provides a general heat stress outlook rather than livestock-specific categories (Table 5.1; Figure 5.9). Descriptions of each index are provided in Table 5.1. Both thermal comfort indices are available as observed and forecast products and are derived from GeoTIFF surfaces of temperature and relative humidity.

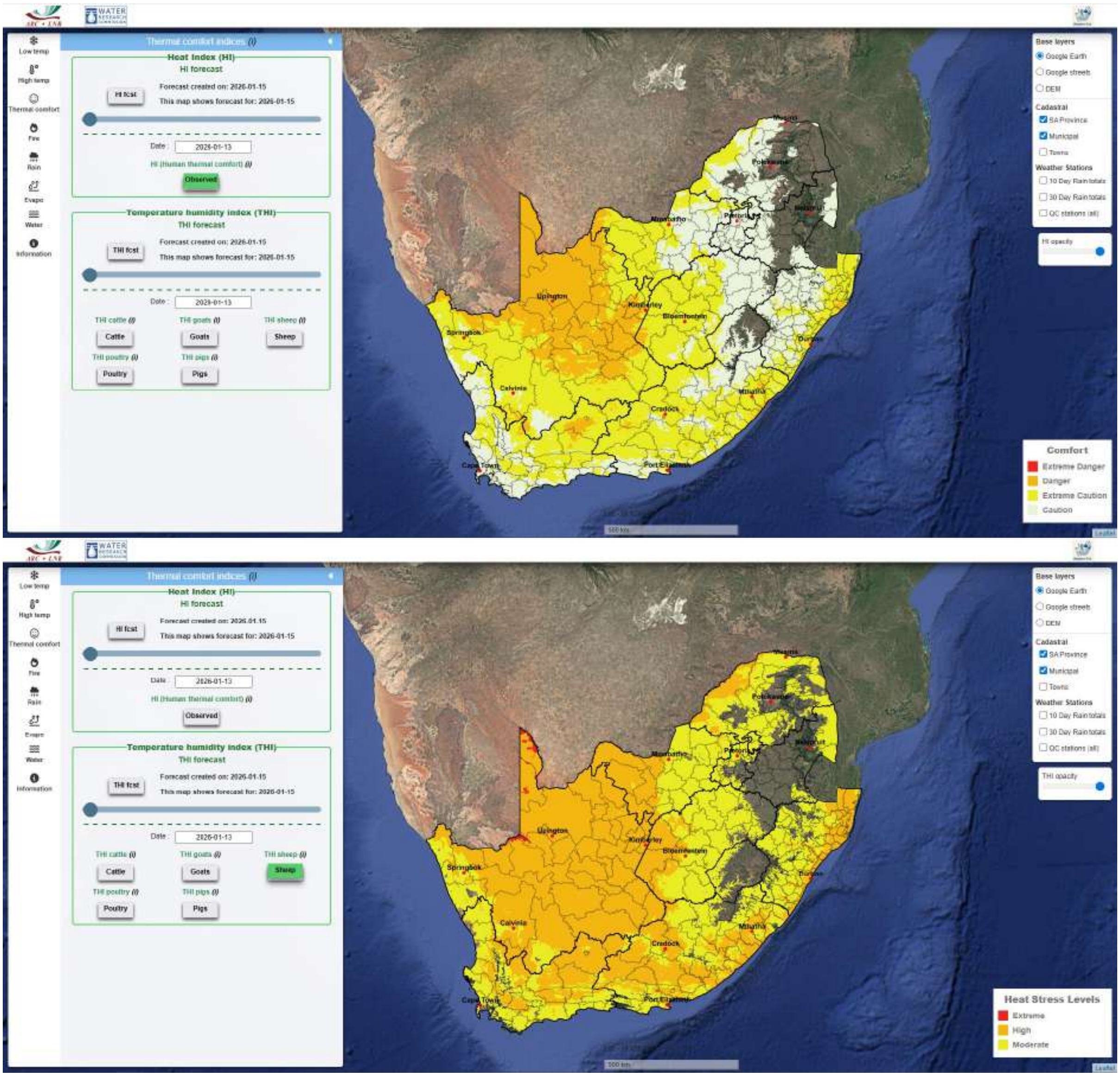

Figure 5.9: Heat index (HI; top) and temperature-humidity index (THI; bottom) for sheep on 13 January 2026, as displayed in the Weather Risk app.

Each thermal comfort index was selected based on its relevance for managing heat-related risks in agricultural environments. The HI provides information on combined temperature and humidity conditions that influence human thermal comfort, supporting decision-making for farm labour management, outdoor work scheduling, and health and safety considerations during hot conditions; for example, elevated heat stress categories may prompt adjustments to working hours, increased rest breaks, or enhanced access to drinking water for farm workers. The THI is particularly relevant for livestock systems, as it reflects the combined effects of heat and humidity on animal thermal stress, productivity, and welfare. Livestock-specific THI categories support management decisions such as providing shade, improving ventilation, increasing water availability, adjusting feeding times, or reducing handling and transport during periods of elevated heat stress. Although the forecast THI is presented as a general heat stress indicator rather than species-specific thresholds, it still provides valuable early warning of developing hot and humid conditions, allowing farmers to implement precautionary measures in advance. Collectively, these indices support proactive management of heat stress risks affecting both people and animals in agricultural systems.

The Weather Risk app includes a fire danger index based on the Lowveld Fire Danger Index (Strydom & Savage, 2017; Figure 5.10), which is available as both an observed and forecast product and is presented in categories of safe, moderate, dangerous, very dangerous, and extremely dangerous, with a detailed description of the index included in Table 5.1. The index is computed using daily gridded GeoTIFF surfaces of rainfall, temperature, relative humidity, and wind speed, reflecting the combined influence of weather conditions on fire risk. This index is an important tool for fire preparedness and response planning in agricultural landscapes. For crop farmers, it supports the safe scheduling of activities such as controlled burns and residue management; for example, planned burns may be postponed when conditions are classified as very dangerous or extremely dangerous. For livestock farmers, the index provides early warning of elevated veld fire risk, supporting timely decisions such as relocating animals, reinforcing fire breaks, or placing staff on standby during high-risk periods. Together, the observed and forecast fire danger products support proactive fire risk awareness and management across agricultural systems.

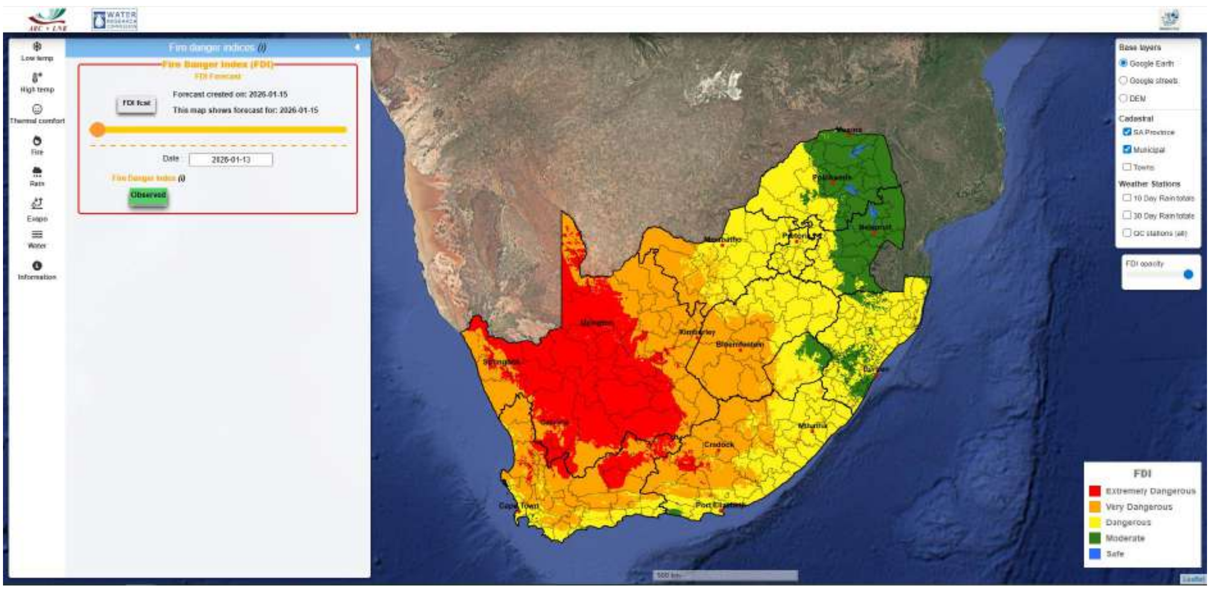

Figure 5.10: Fire danger index for 13 January, as displayed in the Weather Risk app.

The Weather Risk app includes two PET indices (Table 5.1; Figure 5.11). These indices are designed to characterise atmospheric water demand relevant to agricultural water use and management. These indices include: 1) observed and forecast daily PET (in mm), and 2) total observed PET accumulated over the last 10 and 30 days (in mm). PET is computed using the Penman-Monteith equation (Table 5.1; Figure 5.11; Allen et al., 2006), with input variables derived from daily gridded GeoTIFF surfaces of temperature, wind speed, solar radiation, and relative humidity. Descriptions of each index are provided in Table 5.1. Both PET indices are available as observed and forecast products.

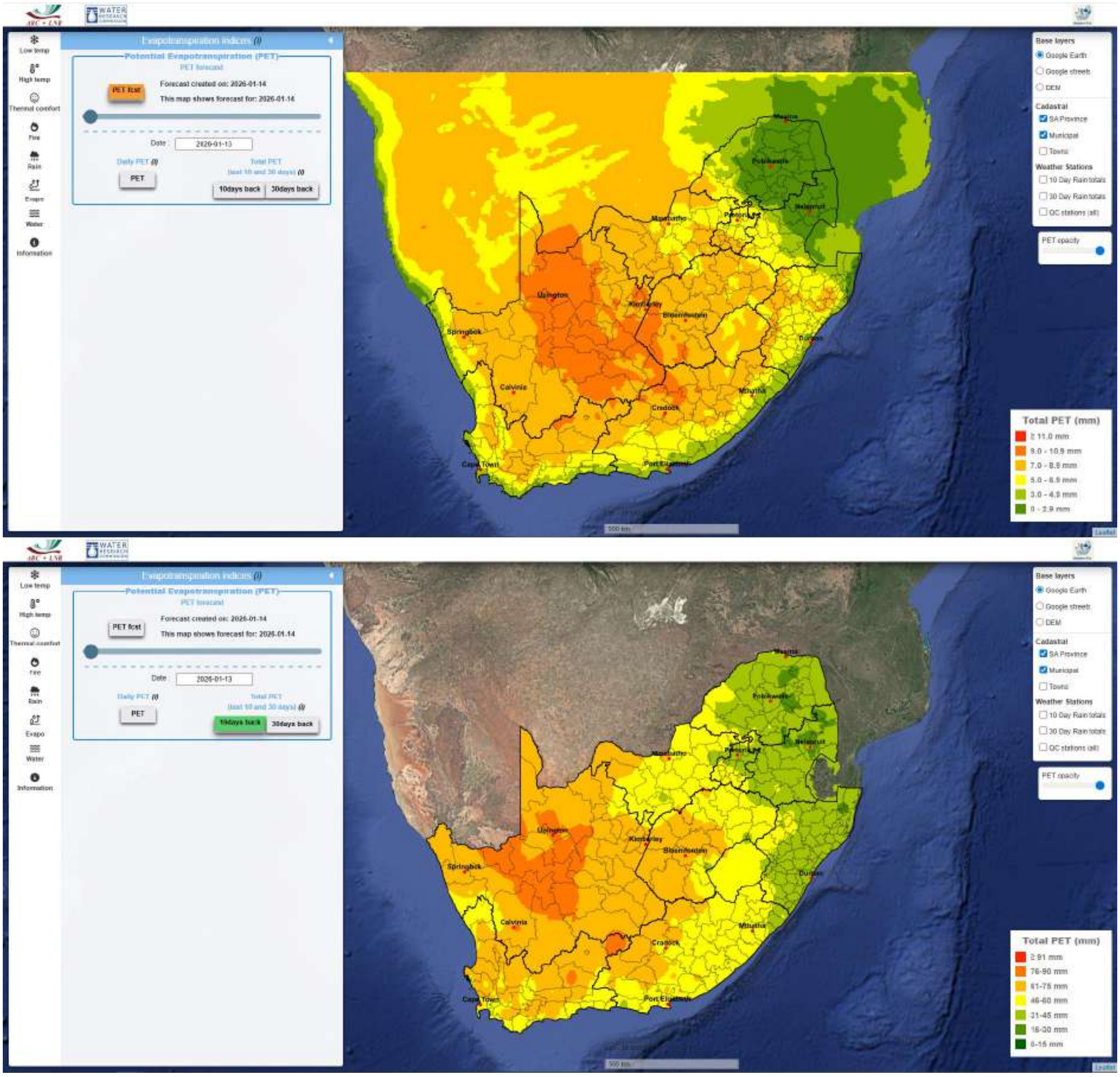

Figure 5.11: Day one of the daily potential evapotranspiration (PET) forecast for 14 January 2026 (top) and total PET (last 10 days) for 13 January 2026, as displayed in the Weather Risk app.

Each PET index was selected based on its relevance for assessing crop and pasture water demand and for supporting water-related decision-making in agricultural systems. Daily PET provides information on short-term atmospheric water demand, supporting day-to-day irrigation planning, particularly during hot, dry, or windy conditions when evaporative losses are high. For crop farmers, this index helps anticipate periods of increased crop water stress and adjust irrigation timing accordingly, while for livestock farmers, it provides insight into daily pasture drying rates and evaporation from watering points. Total PET accumulated over the last 10 and 30 days reflects cumulative evaporative demand and is particularly useful for understanding sustained moisture stress conditions. For crop farmers, this index supports estimation of crop water requirements over short periods, informing irrigation scheduling and water resource allocation. For livestock farmers, high accumulated PET values may indicate accelerated pasture drying and increased pressure on water resources, prompting earlier grazing rotation, supplemental feeding, or closer monitoring of water availability during prolonged dry spells. Collectively, these indices provide complementary information on short-term and cumulative atmospheric water demand, supporting proactive water management across crop and livestock production systems.

The final group of indices included in the Weather Risk app comprises wind-related indices, which are planned additions and are not yet operational (Table 5.1). These indices will include: 1) observed number of days with damaging wind conditions during the last 10 days (in days), and 2) forecast daily number of damaging wind hours. Damaging winds are defined based on the Beaufort wind scale as wind speeds exceeding 17 $m.s^{-1}$, and the indices will be derived from daily gridded wind speed GeoTIFF surfaces. Detailed descriptions of these indices are provided in Table 5.1. Once implemented, these wind indices will provide additional information on short-term wind-related hazards relevant to agricultural activities.

These wind indices are intended to support agricultural risk management by highlighting periods of elevated wind exposure that may disrupt farming operations. For crop farmers, damaging winds can result in crop lodging, increased soil erosion, and difficulties in applying fertilisers or pesticides due to spray drift; advance awareness of such conditions can support preventative actions to minimise potential losses. For livestock farmers, the indices will provide insight into periods of strong winds that may affect grazing conditions, animal welfare, and the stability of shelters and infrastructure. This information will support timely management actions such as reinforcing structures, adjusting grazing plans, or implementing protective measures to reduce wind-related impacts. Collectively, these indices will extend the Weather Risk app's ability to support weather-informed agricultural planning by addressing wind-related risks alongside rainfall, temperature, thermal comfort, fire danger, and evaporative demand.

5.4 Input water data and water indices for the Weather Risk app

At present, under the water tab (see Section 5.5 for further information on the tabs), the Weather Risk app includes four water availability indices, all of which are derived from datasets obtained from external data providers (Table 5.2). Some of these indices are newly calculated using externally sourced datasets, while others are pre-existing products developed and maintained by the respective data providers.

Table 5.2: Details of the water availability indices included in the Weather Risk app.

Index (status of inclusion in the app)	Description as per Weather Risk app
Irrigation extent per quaternary catchment	This index represents the total irrigated land area within each quaternary catchment, expressed as a percentage (%) of the catchment's total area. This index can help farmers, extension officers, and planners to identify the spatial extent and intensity of irrigation activity across catchments. For crop farmers, it offers insight into regional irrigation investment and water demand. For livestock farmers, it may also help in understanding how irrigation influences forage availability or competition for water resources within shared catchments.
Blue water irrigation demand	This index represents the monthly irrigation water demand by showing how much crop water use exceeds rainfall across irrigated fields. Positive values indicate where rainfall is not sufficient to meet crop water needs, signalling greater reliance on irrigation. The index helps crop farmers identify periods and areas with high water demand, plan irrigation more effectively, and prepare for increased pressure on water resources during dry or high-use months.
Monthly surface water anomaly	This index shows how the surface water area for a given month compared to the long-term average for that same month (from January 2016 onwards), expressed as a percentage. It indicates whether water bodies, such as farm dams, are above or below normal levels for the time of year. For crop farmers, it helps assess local water availability for irrigation and supports planting and drought-risk decisions. For livestock farmers, it offers an early signal of potential water shortages or surpluses, informing grazing rotation, stock watering, and livestock movement.
Groundwater Harvest Potential	The Groundwater Harvest Potential Index estimates the maximum volume of groundwater that can be sustainably abstracted per square kilometre each year without depleting the aquifer. It reflects the safe yield of an aquifer under average conditions, indicating how much water can be withdrawn without compromising long-term availability. For crop farmers, the index helps assess the reliability of groundwater as a supplementary or primary irrigation source, supports planning during dry periods, and guides long-term decisions about crop selection, water allocation, and investment in groundwater-dependent irrigation systems.

The first of the water availability indices is the irrigation extent per quaternary catchment (Figure 5.12). This index quantifies the total irrigated land area within each quaternary catchment, expressed as a percentage (%) of the catchment's total area. It provides crop farmers and extension officers, among others, with insight into the level of irrigation development and intensity within a quaternary catchment. This index was derived using the 2023 Field Crop Boundaries dataset, which is a vector dataset, in a shapefile format, developed by the National Crop Statistics Consortium of the National Department of Agriculture. This index is a static index that will only be updated when the field crop boundaries are updated. To create this dataset, irrigated areas were derived by filtering out the specific shapefile field categories of 'Non-pivot Irrigated Annual Crop Cultivation / Planted Pastures', 'Pivot_Irrigation', 'Horticulture', 'Tea_Plantations', 'Shadenet', 'Horticulture_Pineapples' to collectively group them as “Irrigated Fields”. The geometries were then reviewed, validated, and corrected to address invalid features, focusing on resolving overlapping nodes. Using the GIS ‘Intersect’ tool, these irrigated fields were intersected with quaternary catchment boundaries, splitting fields that crossed catchment divides and assigning each resulting segment a quaternary catchment ID. The area of each field segment was calculated, and the segment areas were aggregated to determine the total irrigated area within each catchment, expressed as a percentage. Higher percentage values (i.e., darker blue colours) indicate a higher portion of land area under irrigation in a quaternary catchment (Figure 5.12).

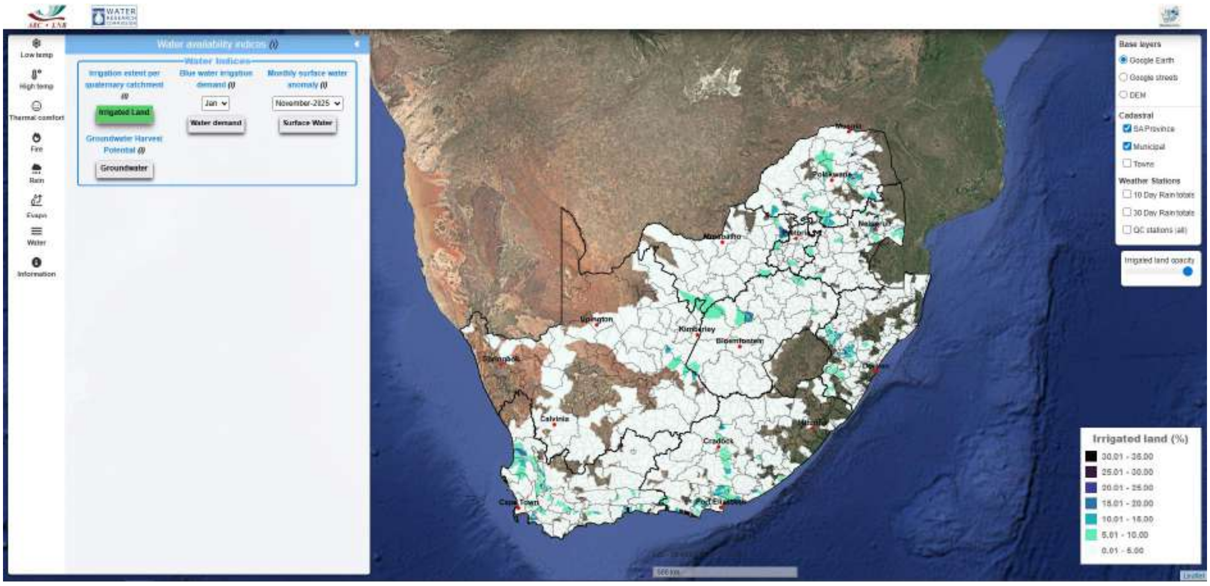

Figure 5.12: Irrigation extent per quaternary catchment, as displayed in the Weather Risk app

The second water availability index included in the Weather Risk app is blue water irrigation demand (Figure 5.13). This index provides insight into the proportion of crop water requirements that must be met by blue water resources, as opposed to green water supplied directly by rainfall. In hydrological and agricultural studies, blue water demand is commonly quantified as the difference between actual evapotranspiration and rainfall (Wu et al., 2024), and serves as an indicator of irrigation dependence and potential water stress. Catchments characterised by persistently high blue water demand are typically more reliant on irrigation and may face heightened risks related to water scarcity or over-extraction of water resources (Khand et al., 2021). When evaluated alongside crop yield information, blue water demand can also provide valuable insights into water-use efficiency/productivity and opportunities to optimise irrigation practices.

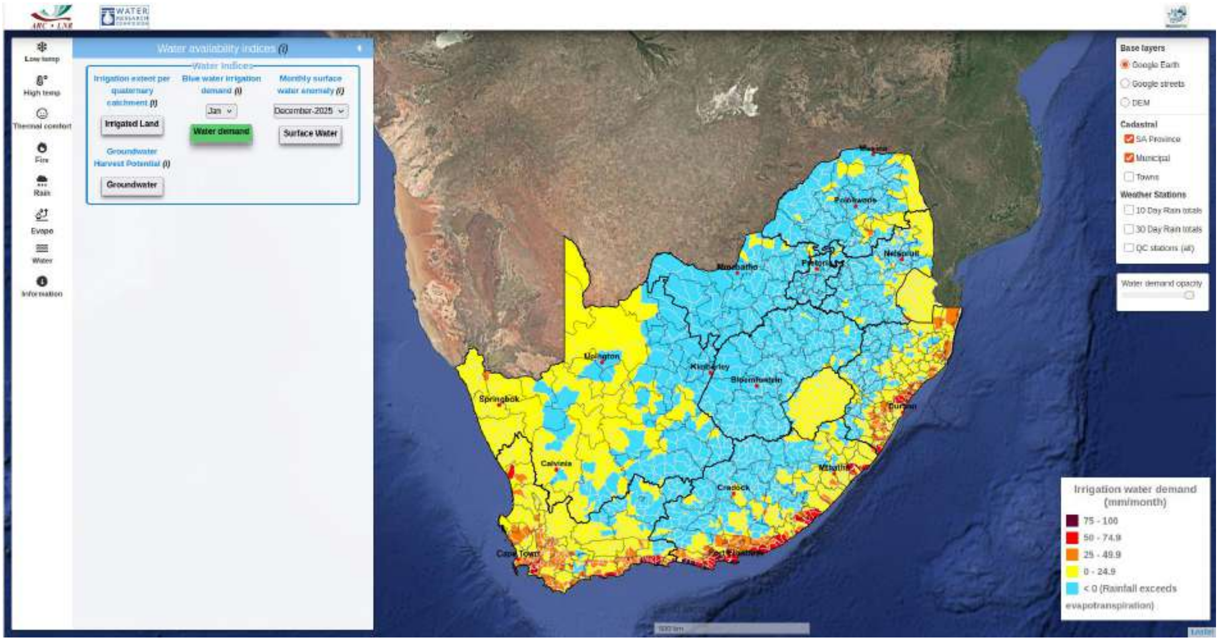

Figure 5.13: Blue water demand for January per quaternary catchment, as displayed in the Weather Risk app.

From an agricultural perspective, this index indicates the degree to which irrigation is required to meet crop water demands across seasons and regions. For crop farmers and extension officers, it supports irrigation planning and water allocation decisions, particularly during periods of low rainfall or high evapotranspiration, while water managers can use it to identify catchments and periods with high irrigation dependence. Livestock farmers may also be indirectly affected, as elevated irrigation demand within shared catchments can increase competition for limited water resources, but can also present opportunities to grow feed under irrigation during droughts.

This index was computed using the Google Earth Engine (GEE) platform and draws on two externally sourced datasets, namely the Moderate Resolution Imaging Spectroradiometer (MODIS) MOD16A2GF actual evapotranspiration (ETa) product (NASA, 2026) and the CHIRPS rainfall dataset (Funk et al., 2015). Within the GEE environment, the MOD16A2GF dataset was used to derive monthly average ETa values, while daily CHIRPS rainfall data were aggregated to monthly rainfall totals. To ensure spatial consistency between datasets, the spatial resolution and projection of the MODIS product were first extracted, after which the CHIRPS dataset was reprojected and resampled to match the MODIS-derived grids. This preprocessing step ensured compatibility between the datasets for subsequent calculations. Using these harmonised monthly datasets, long-term mean values of ETa and rainfall were calculated for each calendar month over the period December 2000 to November 2023. As a result, the blue water demand index represents a static long-term hydroclimatology, reflecting typical seasonal water demand patterns rather than interannual variability. Given its climatological nature, this index is intended to be updated infrequently (e.g., every five years) as longer records become available.

Subsequently, the blue water irrigation demand, representing net irrigation requirements, was estimated as the difference between long-term mean ETa and long-term mean rainfall (i.e., Eta - rainfall). This calculation produced gridded monthly estimates of blue water demand, which were subsequently spatially averaged over each quaternary catchment. Positive values, shown as yellow to maroon in the Weather Risk app, indicate that crop water demand exceeds precipitation inputs, implying a reliance on irrigation water supplied from surface water bodies (such as rivers, reservoirs, and lakes) or groundwater resources (Figure 5.13). Negative values, shown by light blue in the Weather Risk app, indicate that precipitation exceeds crop water demand, reducing, but not necessarily eliminating, the need for irrigation (Figure 5.13). Notably, even where monthly rainfall exceeds ETa, irrigation may still be required if rainfall occurs in short, high-intensity events, leaving extended dry periods during which irrigation is necessary to sustain crops.

The third water availability index included in the Weather Risk app is the monthly surface water anomalies index (Figure 5.14). This index provides a spatially explicit indication of whether surface water availability within a catchment is above or below typical monthly conditions, with direct relevance for both crop and livestock farming systems. In the Weather Risk app, light to darker blue values indicate above-normal monthly conditions at increasing levels, whereas light to darker red values indicate below-normal monthly conditions at decreasing levels (Figure 5.14). From an agricultural perspective, the index serves as a practical indicator of local water availability. For crop farmers, it supports irrigation planning and drought risk management by highlighting periods of reduced surface water storage. For livestock farmers, it provides early warning of potential water shortages or surpluses, helping to guide decisions related to grazing rotation, stock watering, and livestock movement, particularly during unusually dry or wet months.

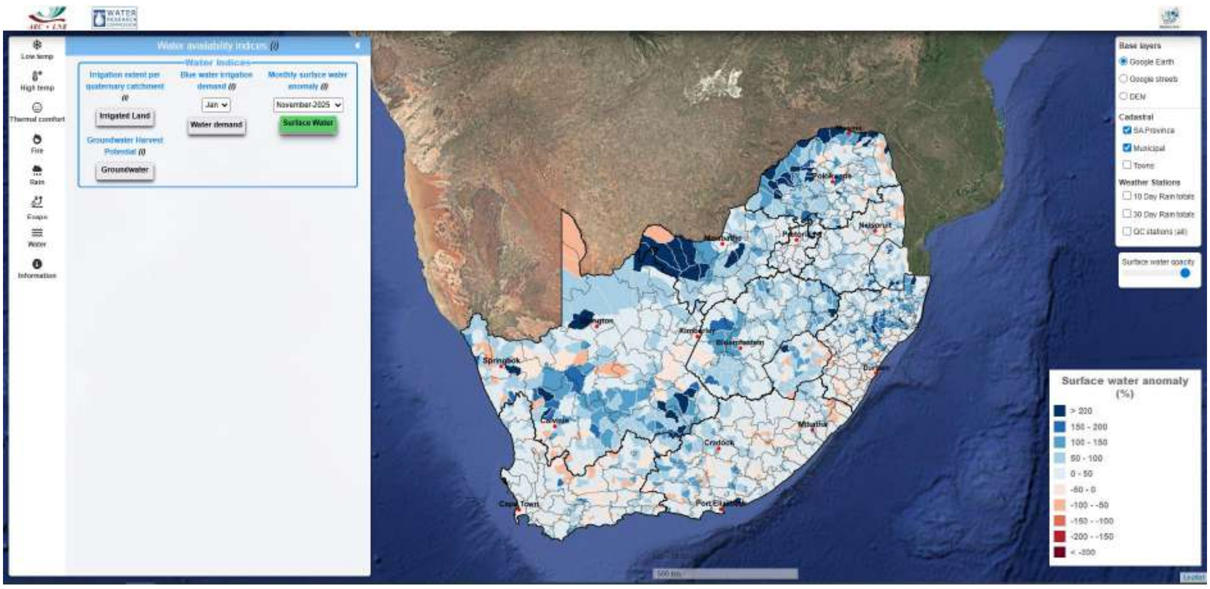

Figure 5.14: Monthly surface water anomaly per quaternary catchment, as displayed in the Weather Risk app for November 2025.

The index is derived from a surface water area dataset based on Sentinel-2 satellite imagery, available from 2016 to the present. This dataset forms part of the National Water Quantity information and is accessible via the mzansiAmanzi platform (see further details of site in Table 2.5). It was developed by GeoTerraImage and EkoSource, with data access provided through the South African National Space Agency (SANSA). Surface water extent is mapped monthly using Sentinel-2 observations to delineate open water bodies such as dams and reservoirs, and is summarised as total surface water area within each quaternary catchment, expressed as a percentage of the catchment area. Full details of the surface water mapping methodology are provided by Thompson et al. (2018), who describe the application of Sentinel-2 satellite imagery for assessing water resource availability at catchment scales.

The monthly surface water anomalies index is calculated by comparing the surface water area for a given month with the long-term average surface water area for the same calendar month, expressed as a percentage (%). Long-term monthly averages are computed using all available data from January 2016 to the present, forming a hydroclimatological baseline. The anomaly is then derived as the percentage difference between the current month's surface water area and the corresponding long-term monthly mean. Positive anomaly values indicate above-normal surface water extent for the time of year, while negative values indicate below-normal conditions. By comparing current water extent to the long-term monthly average, the index highlights whether surface water bodies, such as farm dams, are above or below normal levels for the time of year. The index is updated monthly on the Weather Risk app, with values for the previous month made available on the 15th of each month.

The fourth water availability index included in the Weather Risk app is the groundwater harvest potential index (Figure 5.15). This national-scale dataset was developed by the Department of Water and Sanitation (DWS; DWS, 2026), which granted permission for its inclusion in the Weather Risk app. Although the dataset was originally produced in 2006, it remains the most recent and comprehensive groundwater harvest potential assessment available at a national level.

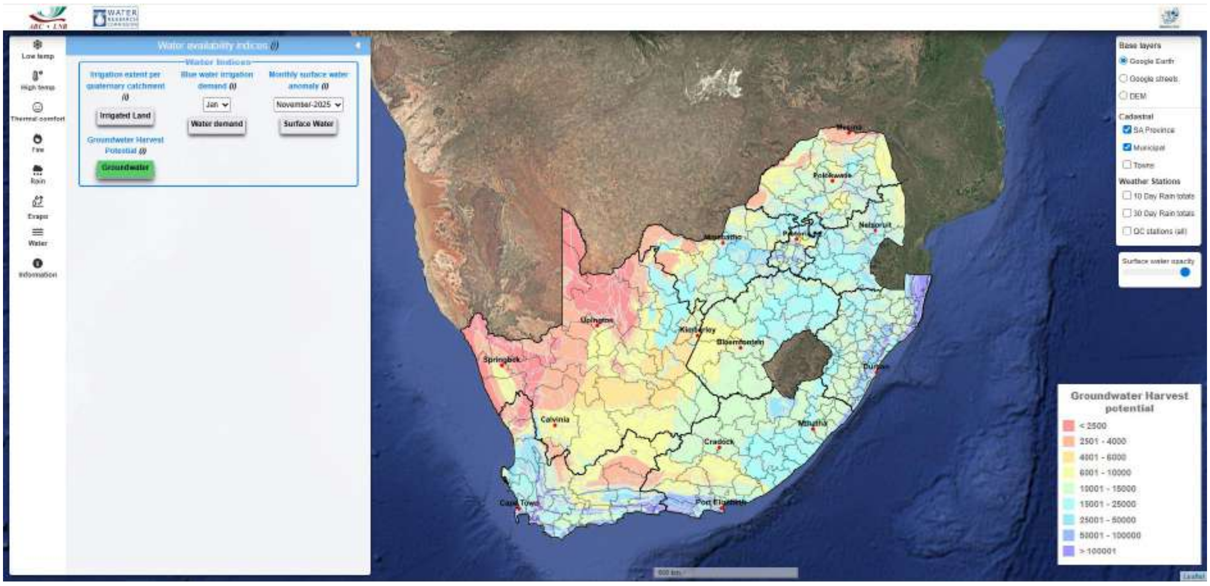

Figure 5.15: Groundwater harvest index, as displayed in the Weather Risk app.

The groundwater harvest potential index estimates the maximum volume of groundwater that can be sustainably abstracted per square kilometre per year without causing long-term depletion of the aquifer. It therefore represents the safe yield of groundwater resources under average climatic conditions, indicating the amount of water that can be withdrawn while maintaining aquifer integrity and long-term availability. The index is summarised spatially at the quaternary drainage region scale and is expressed in units of $m^3.km^2\ year^{-1}$. In the Weather Risk app, higher values shown by darker blue indicate higher levels of groundwater can be safely abstracted in a specific area, while values closer to red indicate lower groundwater levels can be abstracted (Figure 5.15). From an agricultural perspective, this groundwater harvest potential index supports assessments of the viability and sustainability of groundwater as a supplementary or primary water source. For crop farmers, it informs long-term irrigation planning, crop selection, and investment decisions related to borehole development, particularly in water-limited regions. It also assists water managers and extension officers in identifying areas where groundwater abstraction may pose risks to resource sustainability.

The dataset synthesises information on groundwater storage within aquifer systems, estimated recharge rates, and the typical time intervals between recharge events. Full details of the methodology used to derive the groundwater harvest potential are provided in the groundwater resource assessment reports produced by the former Department of Water Affairs and Forestry. While the index does not reflect short-term variability in groundwater levels, it provides a strategic, long-term indicator of groundwater availability and abstraction potential.

In addition to the water availability indices currently included in the Weather Risk app, further indices may be incorporated over time. These may include indicators suggested through user engagement, indices identified as relevant through ongoing research, or new products developed within the ARC Water Science Division. While fewer in number than the weather-based indices, the water availability indices are intended to serve as complementary information, providing a broader hydrological context to support the interpretation and application of weather and climate indices for agricultural decision-making.

5.5 Weather Risk app design and development

The Weather Risk app was developed within a Python programming environment using the *ipyleaflet* package and is designed to display observed and forecast weather information in the form of indices that are updated daily (see Section 5.3.1 and Section 5.3.2), alongside static and monthly updated water-availability indices (see Section 5.4). All weather and water indices are calculated outside of the Weather Risk app as part of the operational processing workflow and are stored on a server for archiving and ongoing use, after which they are accessed and visualised through an interactive, web-based interface that allows users to explore spatial and temporal patterns in the indices without direct interaction with the underlying data processing steps (Figure 5.16).

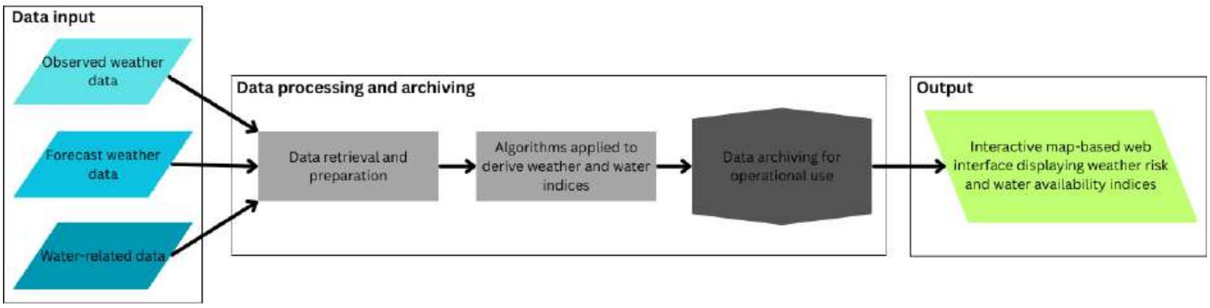

Figure 5.16: Flow diagram illustrating the operation of the Weather Risk app, from input data through processing and archiving to final outputs.

The Weather Risk app is open to the public and can be accessed by anyone via www.weatherrisk.arc.agric.za using a Google Chrome, Microsoft Edge, or Mozilla Firefox browser. At present, users are not required to be registered. While this will be a later requirement, during the current testing phases with the site's public release, users will have access without registering. Upon opening the Weather Risk app in a web browser, users are directed to the home dashboard, which includes an interactive map of South Africa and two side menus containing tabs for the available indices (Figure 5.17).

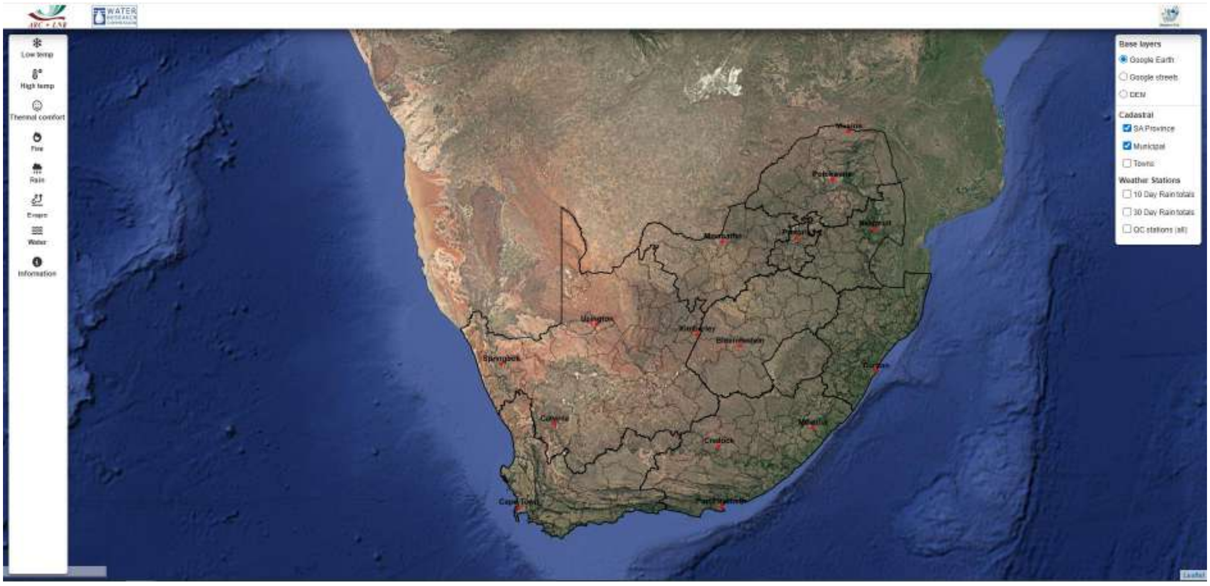

Figure 5.17: Dashboard of the Weather Risk web-based application.

The map of South Africa is used to display indices when one is selected from the left menu, which contains tabs of the different index groups (Figure 5.18), as described in Table 5.1. Among the left menu tabs is an information tab where a user is provided with various pieces of information, such as information about the Weather Risk app, where to find the user guide, and details of the data and contributor acknowledgments, among others (Figure 5.19). To the right is the GIS menu, where a user can choose to display various base layers, cadastral layers, and weather station layers (Figure 5.18).

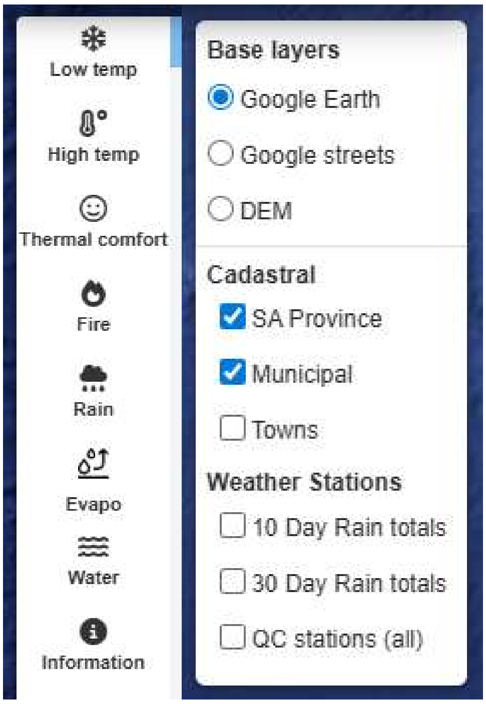

Figure 5.18: Main menus in the Weather Risk app, with the indices and information tabs (left) and GIS layer menu for base layers, cadastral layers, and weather station layers (right).

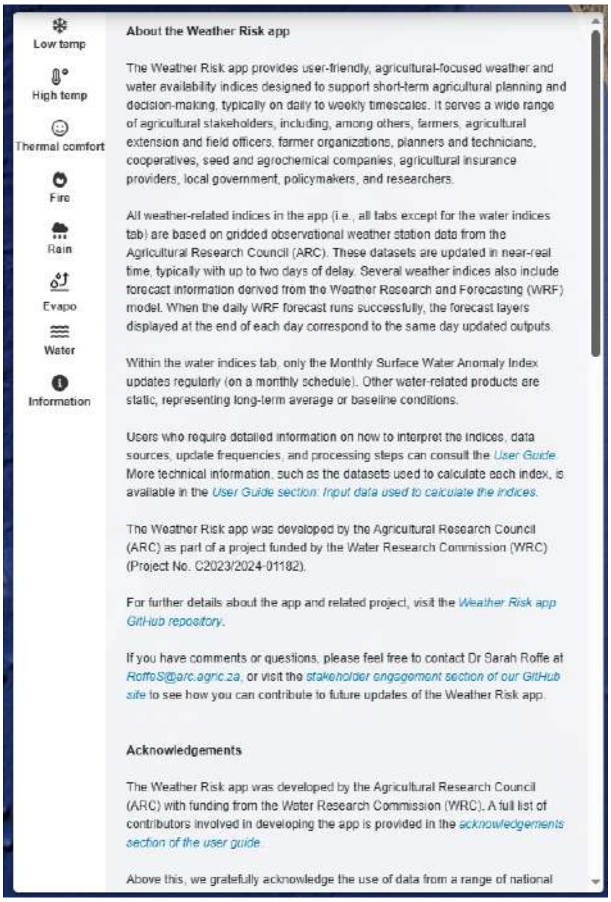

Figure 5.19: The information tab of the Weather Risk app.

When a user hovers over the different icons displayed in the left menu, they can select one of the indices tabs or the information tab (Figure 5.18). A snippet of what is displayed via the information tab is depicted in Figure 5.19. Conversely, Figure 5.20 provides an example of what is displayed when a user selects one of the indices tabs along with a specific index, a pixel, and with the opacity slider adjusted to make the layer transparent to visualise the base layer. In this instance, when an index is selected, a legend is displayed in the bottom right corner (Figure 5.20).

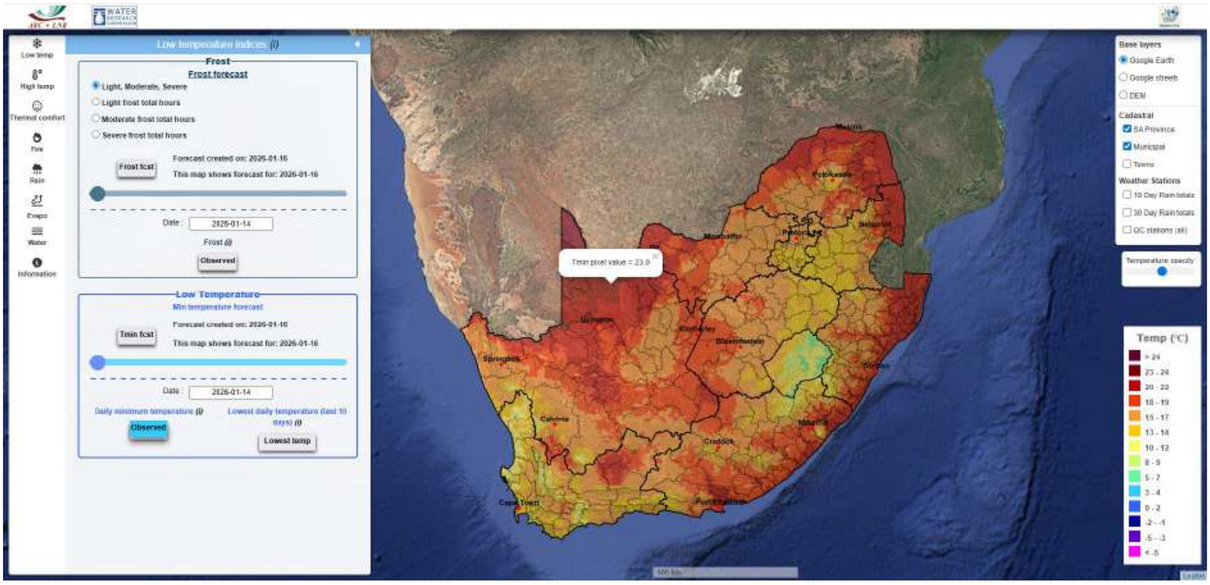

Figure 5.20: Example of a user selecting the daily minimum temperature index for 14 January 2026, with a pixel selected to display the corresponding minimum temperature value, and the opacity slider adjusted to make the layer transparent.

When a user interacts with one of the indices tabs, they interact with one of the three date selection controls, which are used to select dates of the indices displayed in the Weather Risk app (Figure 5.21). For observed weather indices, a user selects the white date box to open a calendar used to select a date, whereas for a forecast, a user interacts with a slider to toggle across the seven forecast days depicted for the specific day, while in some cases, a 7-day total or average of the index is also provided (Figure 5.21). When a user engages with the water indices tab, they select dates using drop-down menus for two of the indices, including the monthly blue water irrigation index and the monthly surface water anomaly index (Figure 5.21). Upon interacting with an index tab, a user can also hover their mouse over index selector buttons to be provided with a description of each of the indices, and to obtain more detailed information, a user can select the (i) next to an index name (Figure 5.22).

Figure 5.21: Date selection controls within the Weather Risk app, showing the date selector for observed weather indices (top), the date selector for forecasted weather indices (middle), and the date selector for water indices (bottom).

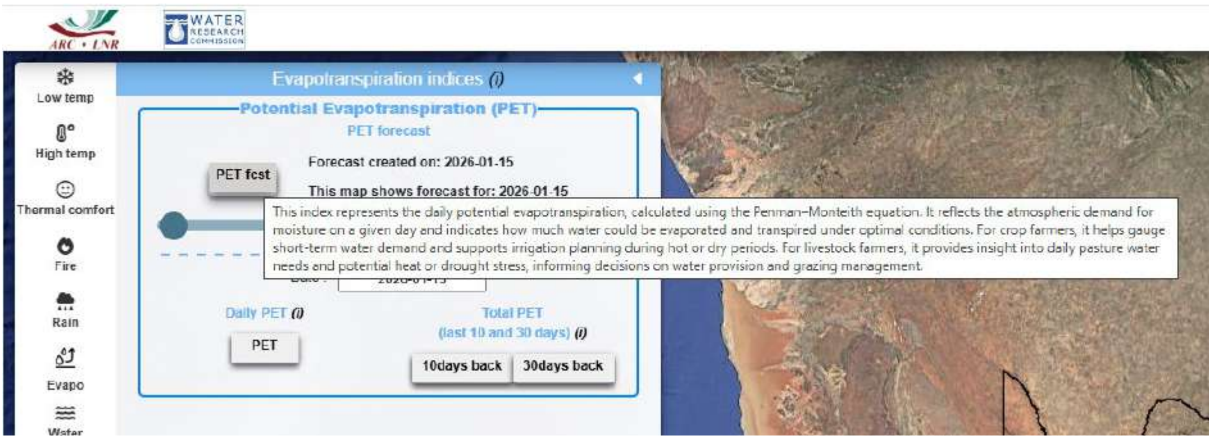

Figure 5.22: Display of an index description when a user hovers over an index selector button in the Weather Risk app

5.5.1 Future additions to the Weather Risk app based on stakeholder feedback

Stakeholder engagement activities conducted throughout the project, including internal feedback workshops held with ARC staff members on 30 September and 1 October 2025, provided valuable insights into potential enhancements that could further improve the usability, accessibility, and decision-support value of the Weather Risk app. Details of these workshops and the feedback outcomes are presented in Chapter 6. In addition to informing the current design and functionality of the platform, these engagements highlighted several priority features that are planned for future development, subject to technical feasibility and available resources.

One of the key suggested additions is the inclusion of a search function within the site. This functionality would allow users to more easily locate areas of interest by searching for town names, farm locations, or geographic coordinates, thereby improving the efficiency with which users can access relevant weather and water availability information for specific locations.

Another important proposed enhancement relates to the introduction of a “points of interest” feature. This would enable users to define specific locations, such as farms, fields, or infrastructure assets, for which tailored advisory information could be generated. Building on both observed and forecasted data, the system could support the delivery of advisory alerts based on predefined thresholds, either system-defined or user-defined. Examples include notifications of forecast rainfall exceeding a specified threshold over a short period, which may increase the risk of waterlogging or operational disruptions. At a minimum, such advisory messages would be delivered via email, with scope for expansion to additional communication channels in future phases.

Feedback from stakeholders also emphasised the importance of improving access to the Weather Risk app across a range of devices. Future development will therefore prioritise optimisation of the site for use on tablets and mobile phones, recognising that many users access weather and climate information in the field or while travelling, rather than exclusively via desktop computers.

In addition to these functional enhancements, the Weather Risk app will continue to evolve in terms of the indices and information products it provides. The inclusion of new weather- or water-related indices will be considered on an ongoing basis, informed by emerging research, stakeholder needs, and the relevance of such indices for agricultural decision-making in South Africa.

To support a co-development approach, mechanisms for ongoing user feedback have been embedded within the project’s public GitHub repository (https://github.com/climindex/hydroclimsa). This platform provides space for stakeholders and users to submit suggestions and comments related to site functionality, content, and usability. While not all suggested additions may be immediately feasible for implementation, all feedback will be reviewed and considered as part of an iterative development process. In this way, the Weather Risk app is not intended to be a static product, but rather a continually evolving platform that will be updated and refined to meet the changing needs of end users and to remain relevant as an operational WCS.

5.6 Weather Risk app user guide and GitHub site

As part of the development of the Weather Risk app, a comprehensive user guide was produced to support effective and consistent use of the platform; this user guide is available on the project's GitHub repository via https://github.com/climindex/hydroclimsa/blob/main/App_user_guide/Weather_Risk_app_user_guide.md. The development of a user guide was explicitly identified in the project scope, recognising that clear guidance is essential for uptake, correct interpretation of indices, and sustained use of WCSs within the agricultural sector.

In addition to hosting the user guide, the project GitHub repository (https://github.com/climindex/hydroclimsa) serves as a central, publicly accessible hub for information related to the Weather Risk app project. The repository provides background on the project objectives and development context, links to the Weather Risk web application and associated documentation, and access to selected example scripts used in the computation of indices. It also supports transparency and collaboration by documenting project outputs, acknowledging project contributors, and providing mechanisms for users to submit feedback or report issues related to the platform. In this way, the GitHub site functions not only as a technical repository but also as an integral component of the project's dissemination, transparency, and user engagement strategy.

Rather than producing a static, standalone PDF manual, the user guide was developed as an online, modular document hosted alongside the aforementioned information provided via the project GitHub repository. This approach was informed by both a review of existing web-based application manuals, such as the Cape Farm Mapper user manual (Western Cape Government Department of Agriculture, 2026), and feedback obtained during stakeholder engagement workshops, which highlighted a preference for concise, easily navigable guidance that users can consult selectively as needed. Hosting the guide online also allows content to be updated as the platform evolves, ensuring that documentation remains current.

The user guide provides structured guidance across several key areas, including: information on the individuals involved in developing the platform and the project funding; an overview of the Weather Risk app and its development context; instructions for accessing and navigating the application; descriptions of the available weather- and water-related indices; an overview of the datasets used to compute these indices; and clear statements on data and application limitations. In addition, the guide outlines forthcoming support material (such as video tutorials), provides instructions for submitting feedback or reporting issues, and includes contact details for user support.

By making the user guide available online, the project ensures that users can engage with only the sections relevant to their needs, while still having access to detailed background information when required. This approach supports usability, transparency, and the long-term sustainability of the Weather Risk app, and aligns with good practice for the delivery of operational weather and climate information services.

5.7 Publicising the Weather Risk app

As noted earlier, the Weather Risk app is live and publicly accessible via www.weatherrisk.arc.agric.za. Publicising of the platform is being undertaken as an ongoing, phased activity and is expected to continue through to March 2026 and beyond.

Publicising activities are being implemented in collaboration with the ARC Public Relations, Marketing, and Communications team and are designed to raise awareness of the platform among key agricultural stakeholders while supporting informed and appropriate use of the site. Planned activities include a dedicated stakeholder engagement event with targeted agricultural stakeholders, as well as broader outreach through digital communication channels and social media platforms managed by the ARC, including Instagram, LinkedIn, Facebook, and X.

Public-facing content developed as part of these activities includes introductory material explaining the purpose and relevance of the Weather Risk app for agriculture in South Africa, explanatory material on weather and climate indices, thematic explainers describing different types of indices available on the site, and practical use-case examples illustrating how the information provided by the platform can support agricultural planning and risk management. The phased approach to publicising the site allows time to both promote awareness of the platform and to observe patterns of use and feedback from early users, which can inform ongoing refinement and improvement of the Weather Risk app.

5.8 Conclusions

This chapter described the development of the Weather Risk app as a web-based agrohydrometeorological indices platform designed to support weather- and water-informed agricultural decision-making in South Africa. It outlined the user-centric design approach adopted for the site, the input weather and water datasets, and the suite of indices developed to characterise rainfall, temperature extremes, thermal comfort, fire danger, atmospheric water demand, and water availability, as well as planned future additions informed by stakeholder feedback.

The chapter also described the design and layout of the Weather Risk app and how indices are presented to users, supported by a dedicated user guide and GitHub repository. Together with the publicising activities described, these components position the Weather Risk app as an accessible and evolving decision-support tool, with scope for continued refinement in response to user needs.

Chapter 6: Stakeholder engagement to test the Weather Risk app

6.1 Introduction

South African farmers operate at the frontline of weather and climate variability, where short-term weather extremes and longer-term climate shifts directly influence production decisions, input costs, and overall farm viability (Maluleke & Mokwena, 2017; Chemura et al., 2022; Olabanji et al., 2020). The agricultural sector is particularly exposed to risks associated with rainfall variability, drought, heat stress, frost, and compound events, all of which can have immediate and cascading impacts on crops, livestock, water availability, and rangeland condition (Yuan et al., 2024). While access to weather and climate data in South Africa has improved substantially over recent decades (Moeletsi et al., 2022), many farmers and agricultural practitioners continue to face challenges in translating raw meteorological information into actionable insights that can meaningfully inform planning and day-to-day decision-making (Myeni et al., 2024). This gap is especially pronounced in contexts where decisions must be made under uncertainty, limited time, and constrained resources, and where specialised climatological expertise is not readily available.

In response to similar challenges internationally, several national meteorological and environmental agencies have developed web-based platforms that aim to improve access to weather information through intuitive visualisation and user-oriented products. Examples include the Australian Bureau of Meteorology's rain radar and weather map services (The Bureau of Meteorology, 2026), which provides near-real-time monitoring of rainfall and weather systems to support, among others, agricultural and disaster-risk decision-making, and the Meteorological Service Singapore's current observations platform (Meteorological Service Singapore, 2026), which presents rainfall and surface weather information in a format accessible to both technical and non-technical users. These platforms demonstrate the value of moving beyond traditional data dissemination toward tailored, user-focused tools that prioritise interpretability, relevance, and ease of use. However, such systems must be carefully designed to reflect local weather and climatic conditions, sector-specific needs, and user capacities if they are to be effective in supporting agricultural decision-making.

The Weather Risk app was developed within this context, with the explicit aim of improving access to weather- and water-availability information that is directly relevant to agricultural risk management in South Africa. The site provides users with free access to a suite of weather and water availability indices derived from gridded observational, forecast, and satellite datasets, presented through an interactive web interface. These indices are designed to summarise complex meteorological and water-related information into metrics that are more easily interpreted in relation to agricultural activities, such as planting, grazing management, water planning, and livestock heat-stress risk. By focusing on indices rather than raw variables alone, the Weather Risk app seeks to bridge the gap between weather and climate science and practical decision-making, supporting a wide range of agricultural stakeholders, including farmers, extension officers, advisors, and policy practitioners.

Importantly, the usefulness of such a platform cannot be assumed solely based on technical robustness or scientific credibility (Walker, 2020). For such a system to be effective, it must align with user needs, be intuitive to navigate, present information at appropriate spatial and temporal scales, and communicate risk in a manner that is meaningful to its intended audience (Vaughan et al., 2019). User engagement and feedback are therefore essential components of the development process, ensuring that the platform evolves in response to real-world requirements rather than purely technical considerations. This is particularly critical in the South African agricultural context, where users represent a diverse range of production systems, climatic regions, and levels of technical expertise.

At the time of this stakeholder engagement activity, the Weather Risk app was not yet publicly accessible due to outstanding Secure Sockets Layer (SSL) certification requirements. To ensure that user testing and feedback could still be undertaken within the project timeframe, an internal stakeholder engagement meeting was convened with ARC staff. This meeting brought together participants familiar with agricultural decision-making and the use of weather and climate information in agricultural contexts, providing an opportunity to test the site's functionality, clarity, and relevance prior to public release. The engagement focused on assessing whether the indices, visualisations, and supporting descriptions were understandable, whether the site was perceived as useful for agricultural planning and risk reduction, and how the platform could be improved to better meet user expectations.

The results presented in this chapter contribute to Objective 3 of this research project and reflect feedback obtained during this internal stakeholder engagement process. They provide critical insights into how users interact with the Weather Risk app, how effectively the platform communicates weather- and water-related risk, and where refinements are needed to enhance usability and applicability. By systematically evaluating user perceptions at this stage, the project aimed to strengthen the final design and functionality of the Weather Risk app, ensuring that it is well-positioned to support weather- and water-informed decision-making once made publicly available.

6.2 Data and methodology

To test and gather feedback on the Weather Risk app, two one-day workshops were hosted with ARC staff members from a wide range of disciplines. These workshops took place on 30 September 2025 and 1 October 2025 and were strictly internal because an SSL certificate (i.e., a digital file that secures a website by encrypting data between a user's browser and the server) had not yet been obtained for the site. Consequently, the site was only accessible via the ARC network.

With the aim of sharing the Weather Risk app for full functional testing and to gather feedback for site improvement, these workshops were hosted both in person and online, with a total of 14 and 11 attendees on 30 September and 1 October, respectively (Figures 6.1-6.2). Each workshop commenced with a welcome and participant introductions, followed by a presentation on the background to the Weather Risk app. Thereafter, a guided walk-through of the app was conducted using the user manual/guide. This session also allowed time for attendees to provide verbal feedback on the app. Attendees were then allowed to explore the app independently while completing an online questionnaire accessible via https://forms.gle/jqmEw4dosZ7q3EVf9.

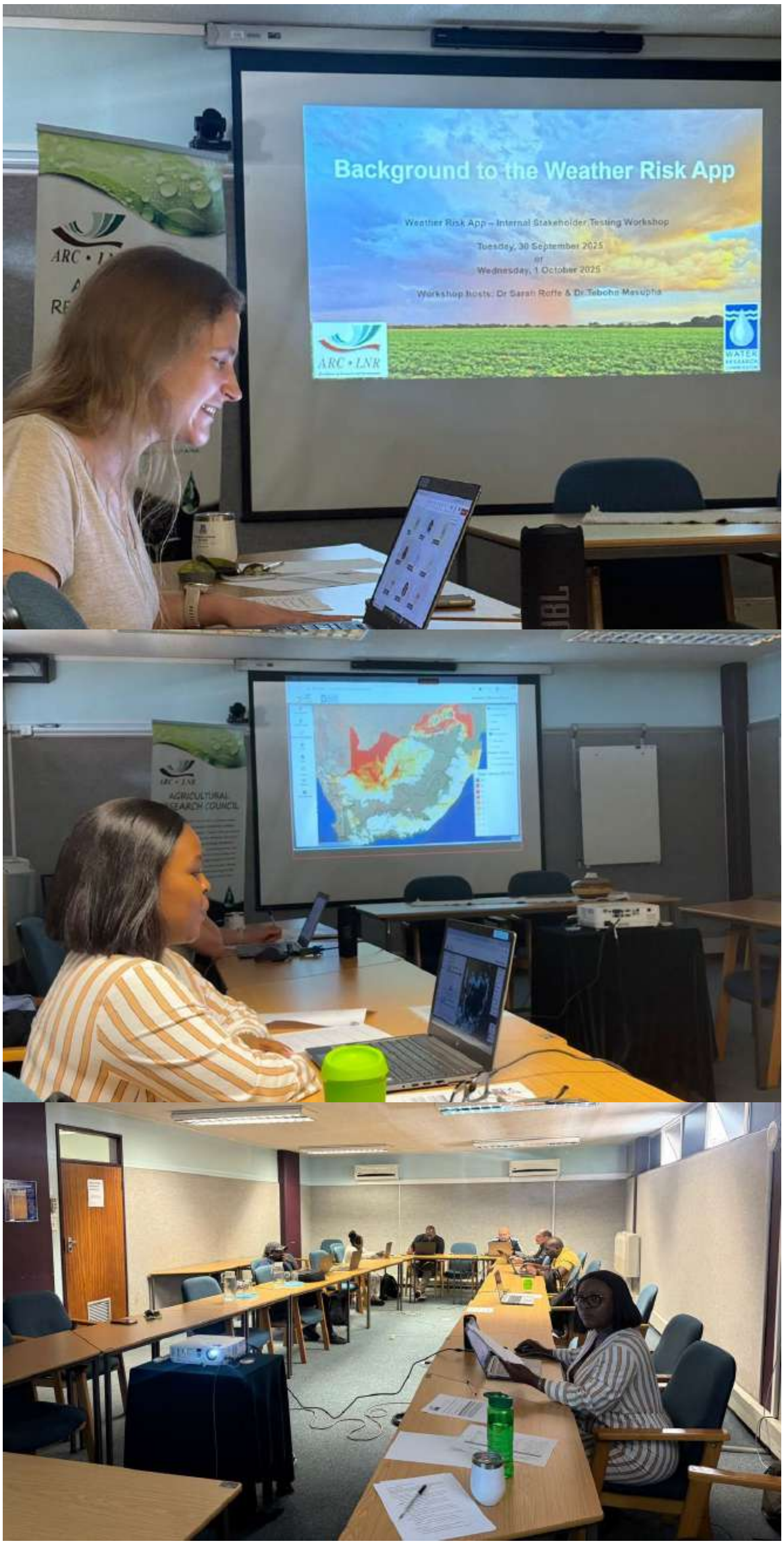

Figure 6.1: Photographs from the Weather Risk app user-testing workshop held on 30 September 2025. The top panel shows the presentation of the background and objectives of the Weather Risk app, the middle panel shows the live demonstration of the Weather Risk app, and the bottom panel shows the workshop attendees.

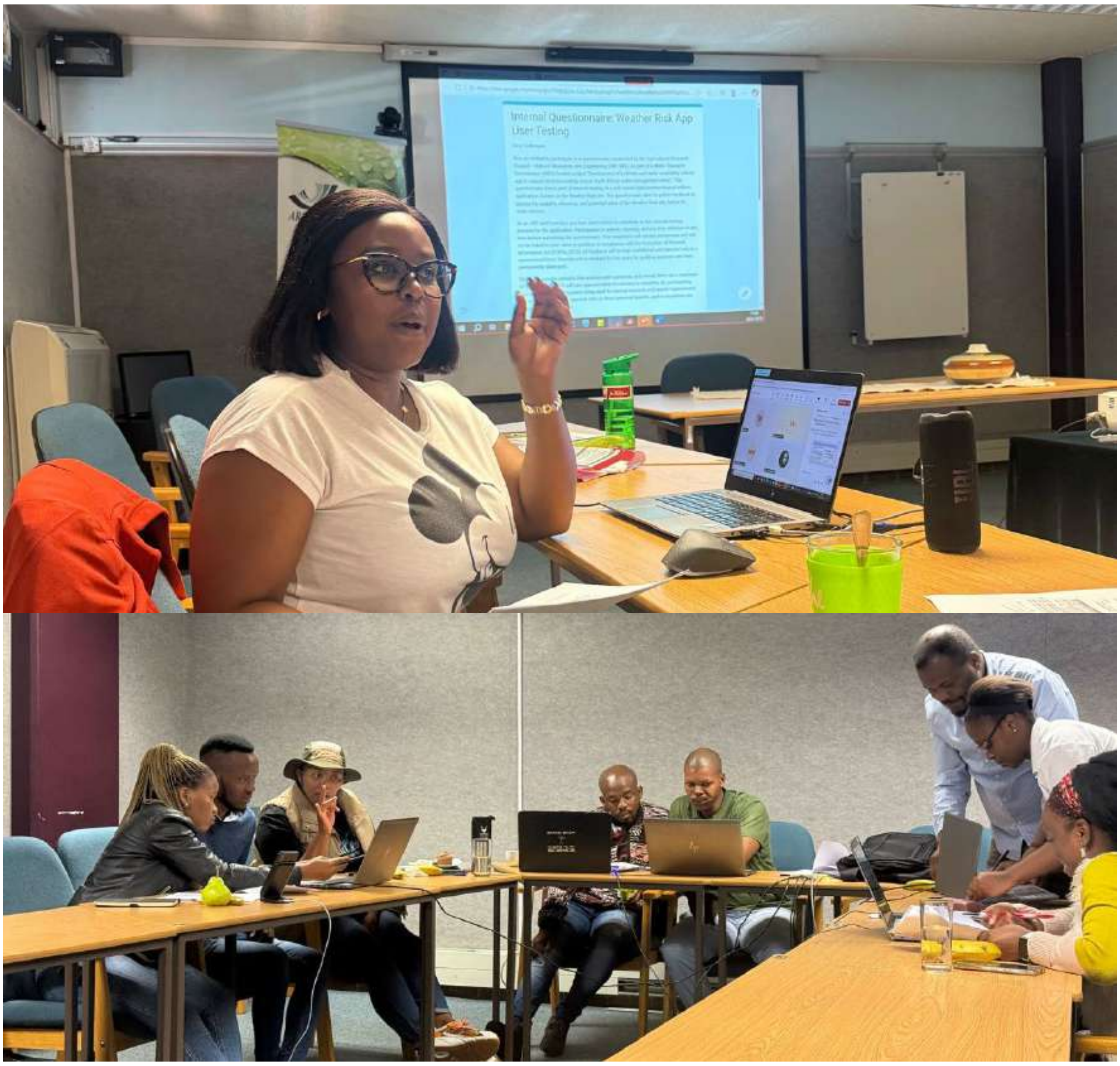

Figure 6.2: Photographs from the Weather Risk app user-testing workshop held on 1 October 2025. The top panel shows the questionnaire session of the workshop, and the bottom panel shows the workshop attendees.

This questionnaire was administered as a structured online survey, divided into five sections with a total of 38 main questions and 24 sub-questions, depending on respondents' answers. The sections of the questionnaire explored: 1) user demographics, to assess how respondents' backgrounds and work contexts may influence their use of and engagement with the app; 2) usability, functionality, and user experience, to assess how intuitive, functional, and user-friendly the Weather Risk app is, as well as the usefulness of the user manual; 3) relevance and usefulness of the app, to assess whether the information provided is relevant to respondents' work or the work of others in the field; 4) perceived impact and value of the app, to assess views on the potential benefits or added value of the system; and 5) gaps, suggestions, and additional feedback, allowing respondents to suggest improvements, request new features, or share any additional comments on the app.

A total of 23 attendees completed the questionnaire. All responses underwent data-quality processing to flag incomplete or suspicious questionnaire submissions. No incomplete or suspicious questionnaires were detected, primarily because all questions were compulsory to complete, most questions were multiple choice, and all questions were completed collectively during the allocated workshop session devoted to the questionnaire. Of all the questions an attendee could answer, 38 questions were analysed for this report.

The analysed questions included a mix of closed- and open-ended questions. All responses were summarised as frequencies converted to percentages. Responses to closed-ended multiple-choice questions allowing only one answer totalled 100%, while those allowing multiple answer choices totalled more than 100%. All multiple-choice questions included an "other" option requiring further explanation; these responses were either grouped within existing response categories or used to create new response groupings. Open-ended questions were summarised using a thematic coding approach, whereby responses were grouped into thematic categories and analysed in the same manner as the closed-ended questions.

6.3 Results and discussion

6.3.1 Respondent background and use of weather and climate information

Figure 6.3 summarises respondents' engagement with weather and climate information, including whether they use such information directly or support others (e.g., farmers or advisors) who use it, how frequently it is accessed, and the purposes for which it is applied. Almost all respondents (95%) indicated that they either use weather and climate information themselves or support its use by others (Figure 6.3a), highlighting a stakeholder group that is already actively engaged in weather- and climate-informed decision-making. The frequency of engagement with weather and climate information varies across respondents, ranging from ad hoc use for specific projects (5%) to very frequent use on a daily or almost daily basis (38%; Figure 6.3b). Importantly, 86% of respondents reported engaging with such information at least monthly (Figure 6.3b). This widespread and relatively frequent use emphasises the importance of providing information at shorter temporal scales and supports the need for weather-scale indices, reinforcing the relevance of the Weather Risk app.

Respondents reported multiple applications of weather and climate information (Figure 6.3c). While research, analysis, or academic use was the most common application (67%), substantial proportions of respondents also use this information to anticipate or manage climate-related risks such as droughts, floods, and heatwaves (45%), to assess land, natural resources, or site suitability for crops, livestock, or infrastructure (43%), and to inform or support decisions made by farmers, clients, or other stakeholders (43%; Figure 6.3c). These results indicate that weather and climate information are widely used for both analytical and applied decision-making purposes.

Figure 6.4 provides insight into respondents' familiarity with web-based weather and climate information tools and the platforms they commonly use. Familiarity with such tools is generally high, with only 5% of respondents indicating that they are not familiar with web-based platforms (Figure 6.4a). In contrast, 41% reported being very familiar and a further 41% somewhat familiar, meaning that 82% of respondents have at least a moderate level of experience using online weather and climate tools (Figure 6.4a). Respondents reported using a range of platforms, most notably the SAWS web portal (61%) and Windy (50%; Figure 6.4b). The use of multiple platforms suggests that users draw on different sources to meet diverse information needs, underscoring the value of the Weather Risk app as a complementary, agriculture-focused platform that integrates weather and water availability information.

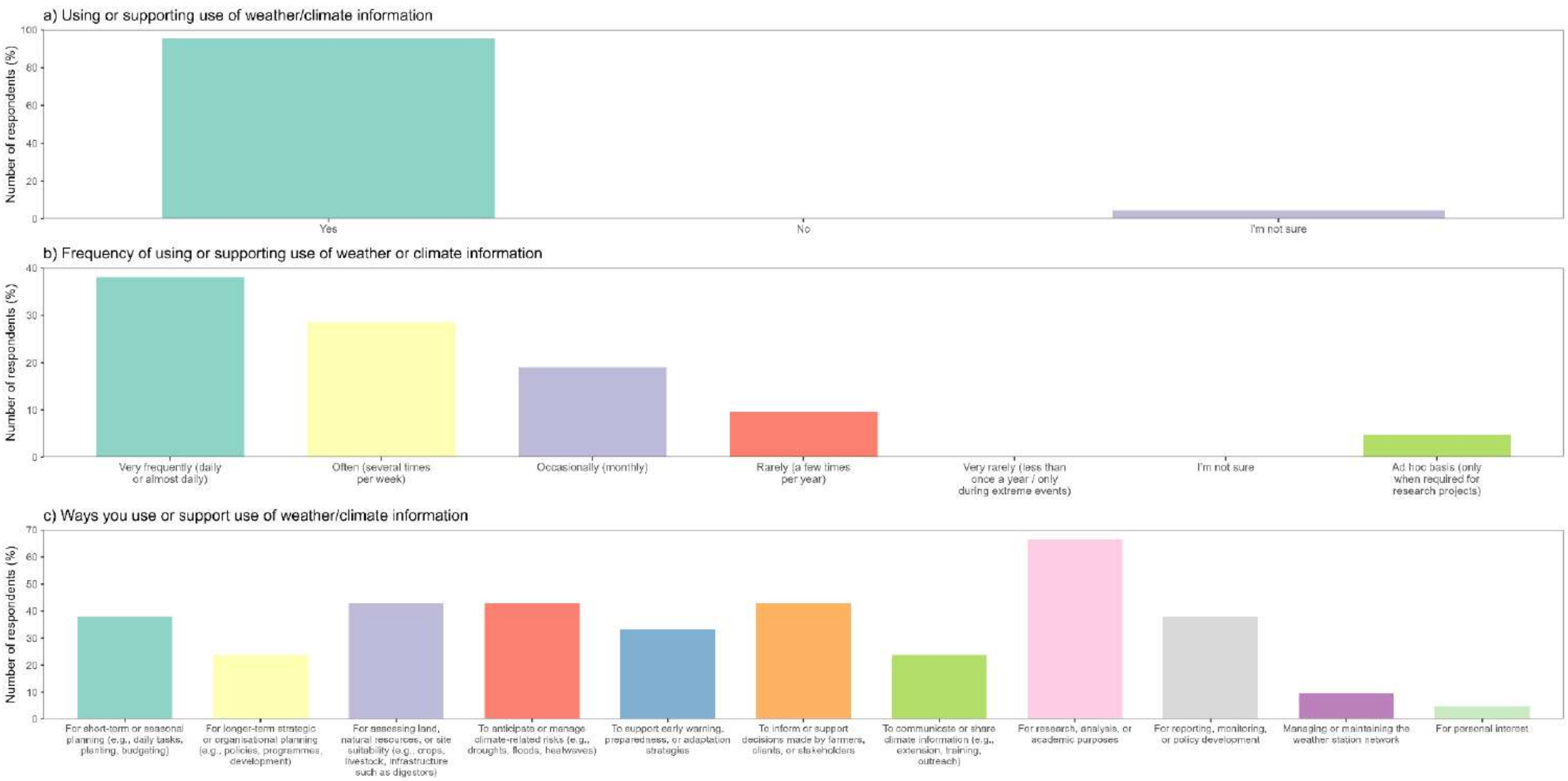

Figure 6.3: Responses showing a) whether respondents use weather and climate information or support users who do so, b) how frequently this information is used or supported, and c) the main ways in which respondents use or support the use of weather and climate information.

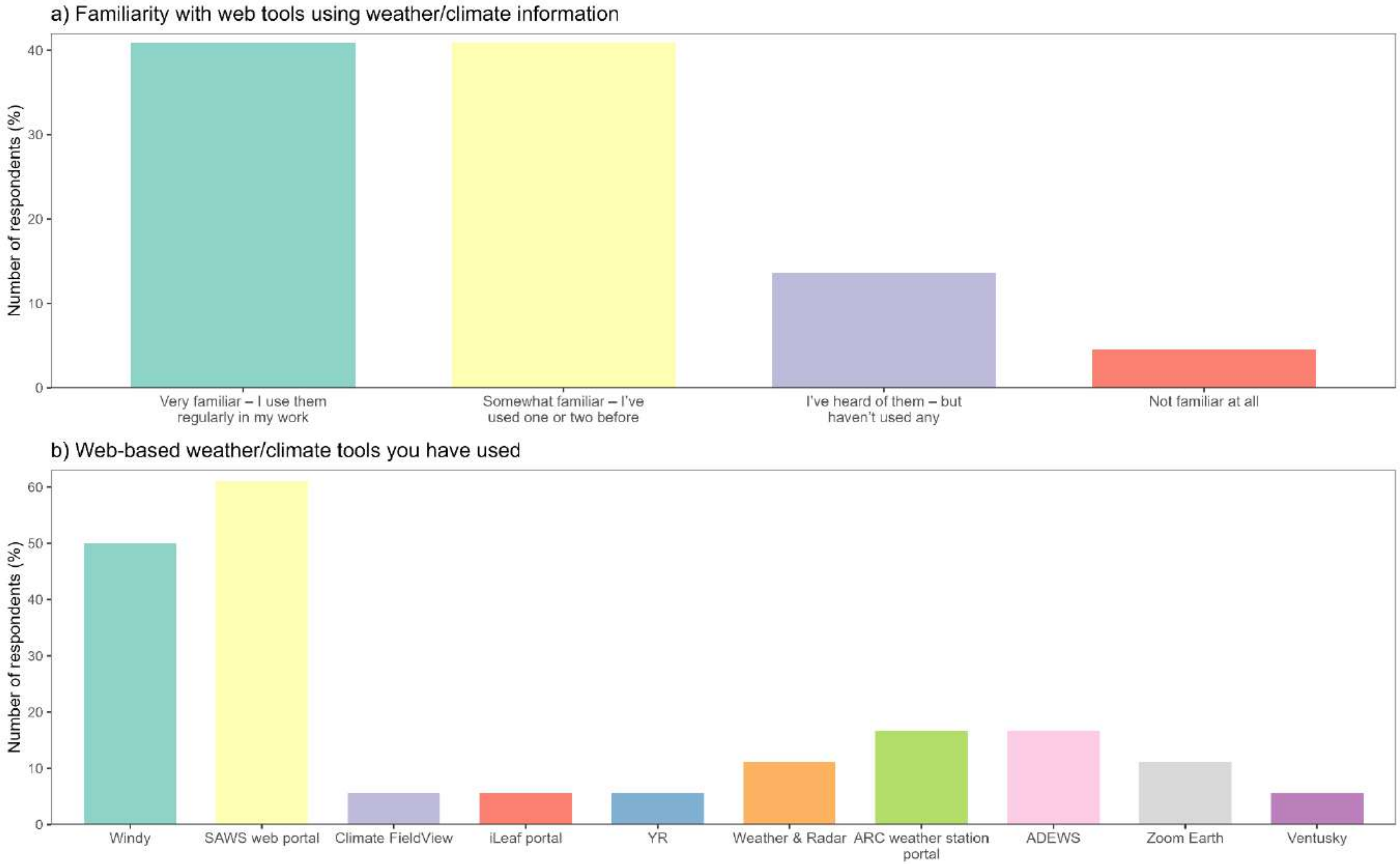

Figure 6.4: Responses showing a) respondents' familiarity with weather and climate information web tools, and b) the specific web tools they have previously used.

6.3.2 Usability, navigation, and visual interpretation of the app

Figure 6.5 summarises respondents' perceptions of the overall usability of the Weather Risk app, including app rating, ease of finding and interpreting information, ease of navigation across indices and data types, and whether any components of the app were confusing or difficult to use. Overall perceptions were positive, with nearly half of respondents rating the app as very good (46%), and a further 23% rating it as fair, indicating generally favourable user experiences despite the app still being under development (Figure 6.5a).

Most respondents indicated that the information presented in the app was easy to find and interpret (73%), while 22% and 5% reported that it was somewhat and not easy to do so, respectively (Figure 6.5b). Feedback from respondents who indicated "somewhat" or "no" highlighted areas for improvement, primarily related to clarity and accessibility for non-technical users. Common themes included the need for simpler wording for farmer-level interpretation, clearer explanations of terms such as "hottest", "coldest", and "water demand", improved interpretation of colours, numbers, and legends, and the absence of a search function to support navigation. Importantly, these explanatory comments, together with similar feedback provided in response to later questions, have been and continue to be used to guide ongoing refinement and improvement of the Weather Risk app.

Navigation across the indices and data types available in the app was generally perceived as straightforward, with 91% of respondents indicating that the app was easy to navigate and a further 9% reporting that it was somewhat easy (Figure 6.5c). Explanatory comments associated with the "somewhat easy" responses largely reflected the learning curve associated with a new platform or isolated issues encountered during testing, including unexpected variable displays and possible instability related to the app's developmental stage.

When asked whether any parts of the app were confusing or difficult to use, half of the respondents (50%) indicated that there were no confusing components, while 41% reported that some parts were confusing or difficult, and 9% indicated this was somewhat the case (Figure 6.5d). Feedback from respondents who identified difficulties consistently pointed to a small number of recurring issues, including confusion around date selection and forecast day labels, inconsistent behaviour of legends when switching between indices, unclear indication of missing or no-data areas, and difficulty interpreting certain thresholds, particularly for water demand. Several respondents also reiterated the need for clearer guidance within the app, such as explanatory text or tooltips, to assist users in understanding what is being displayed and how different tabs and indices should be interpreted.

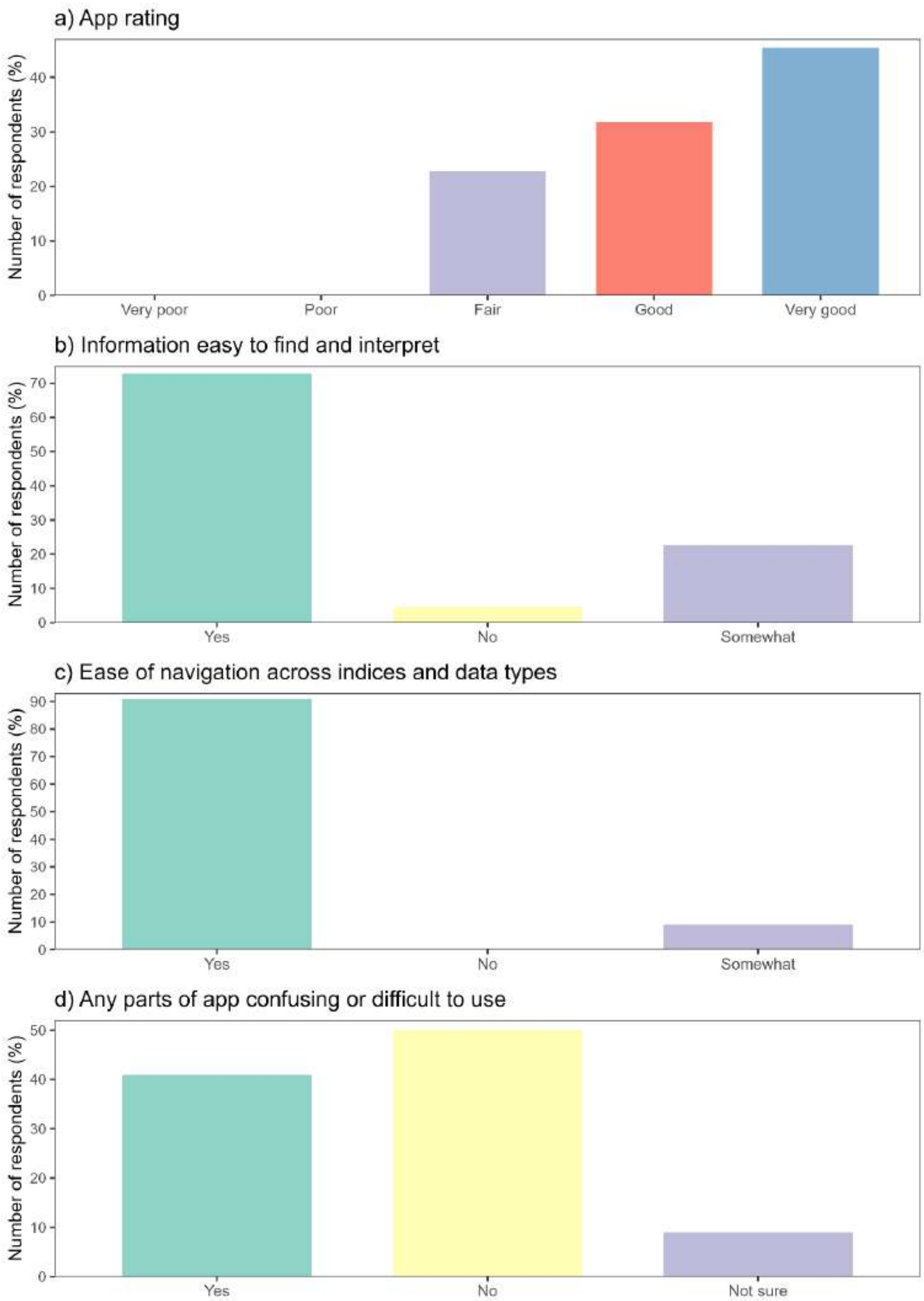

Figure 6.5: Responses showing a) the overall rating of the Weather Risk app, b) whether the information in the app is easy to find and interpret, c) whether the app is easy to navigate across different indices and data types, and d) whether any parts of the app are perceived as confusing or difficult to use.

Figure 6.6 summarises whether respondents used the user manual/help guide and, if so, how useful it was. Only 18% of respondents reported using the manual, while 64% did not use it (Figure 6.6a). This likely reflects that the app was perceived as reasonably intuitive to navigate, supported by the live demonstration during the stakeholder session. A further 18% indicated that they were not aware of the manual (Figure 6.6a), despite a PDF version being shared, suggesting that the guidance material needs to be more visible and easier to access within the app environment. In response, the manual has since been placed online (via GitHub), and a direct link has been added to the site. These results also support the value of developing additional user-support resources, particularly a short video guide, which is planned to complement the written manual.

Among the respondents who used the manual, perceptions of usefulness were strongly positive, with 75% indicating that it was very helpful and 25% indicating that it was moderately helpful. (Figure 6.6b) Suggestions for improvement focused on making the guidance more embedded, targeted, and easier to digest. Respondents recommended integrating help functions directly into the app interface (e.g., an information button linked to the selected index), enabling direct links from each index view to its relevant description, and restructuring the manual into shorter, more focused guides. Additional recommendations included presenting guidance in a step-by-step format using bullet points or numbered steps to improve usability for a broader range of users.

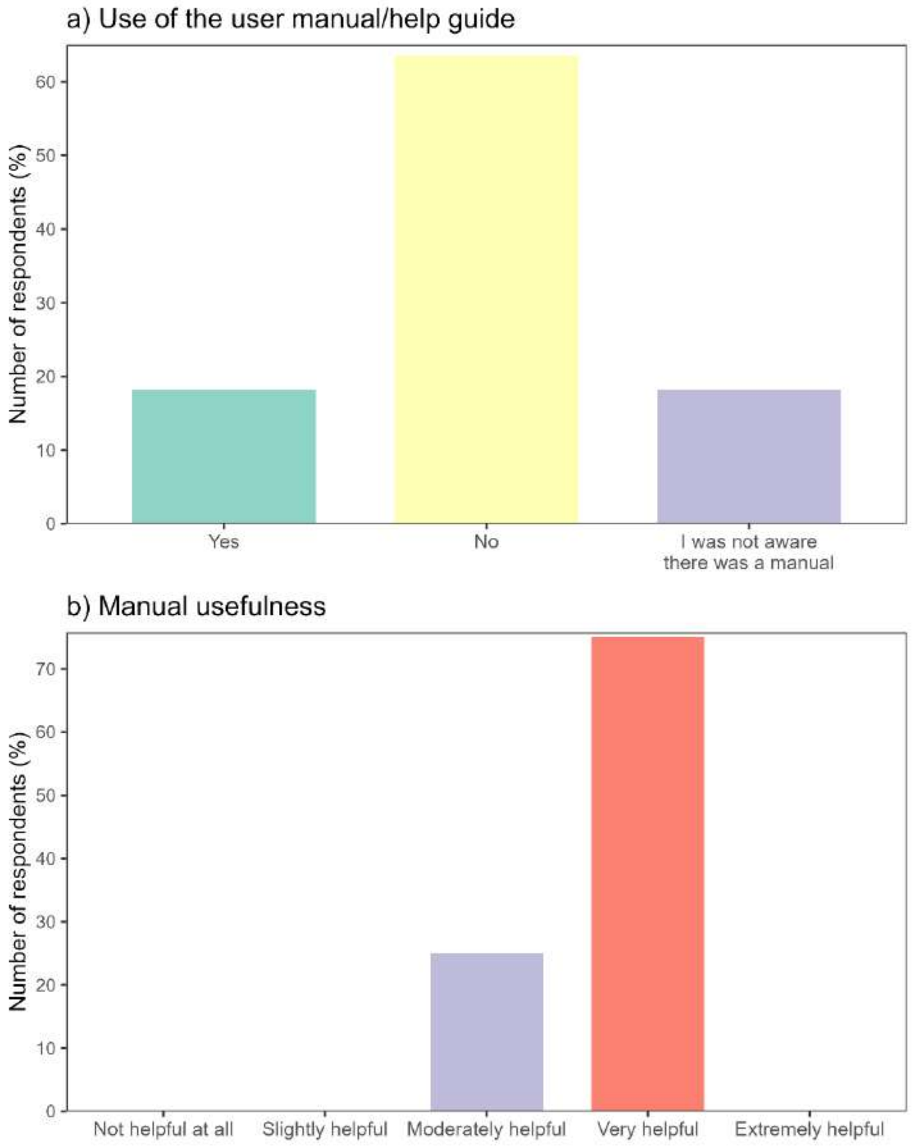

Figure 6.6: Responses showing a) whether respondents used the user manual/help guide, and b) whether the manual was perceived as useful.

Figure 6.7 summarises respondents' perceptions of the interpretability of index colour schemes and the clarity of index descriptions within the Weather Risk app. Most respondents (82%) indicated that the colours used in the app were helpful and easy to interpret, while 14% reported that they were somewhat easy and only 5% indicated that they were not easy to interpret (Figure 6.7a). Feedback from respondents who expressed some difficulty primarily related to clarity of legends and colour distinctions, particularly for no-data values and for conveying levels of risk. Suggestions included improving legend explanations, using more clearly contrasting colours for no-data areas, and aligning colour conventions with intuitive risk signaling (e.g., green for favourable conditions and red for warning or high-risk conditions). These comments have informed ongoing refinements to colour schemes and legend presentation within the app.

Figure 6.7b shows responses related to the availability and clarity of index descriptions. Most respondents (68%) reported that they were able to find the index descriptions, and among these respondents, 80% indicated that the descriptions were clear and understandable, while 20% reported that they were somewhat clear (Figure 6.7b). Feedback associated with the "somewhat" responses highlighted a need for more concise descriptions, particularly at the start of the text, clearer explanations for certain indices (notably water demand), and reduced use of technical jargon or the inclusion of supporting links where jargon is unavoidable. In response to this feedback, index descriptions have been reviewed and shortened to improve clarity and accessibility, particularly for non-technical users.

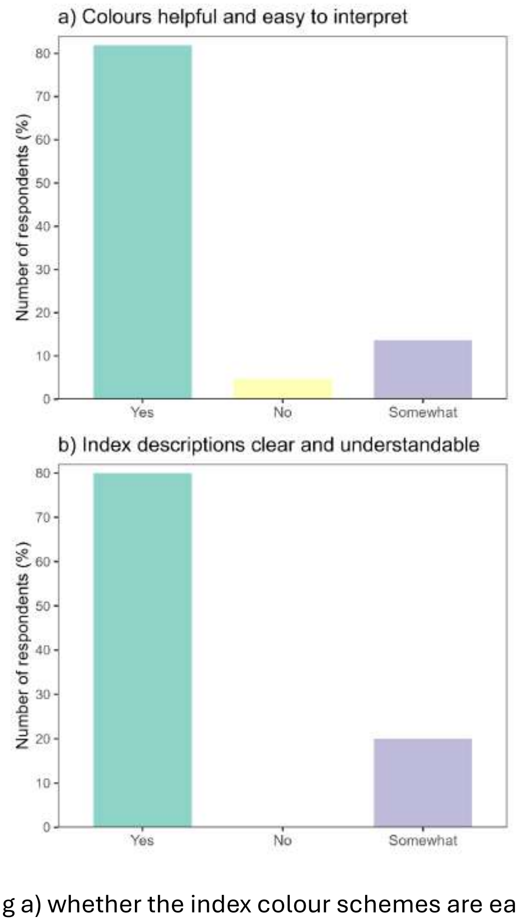

Figure 6.7: Responses showing a) whether the index colour schemes are easy to interpret, and b) whether the index descriptions are clear and understandable.

6.3.3 App functionality and perceived usefulness of indices

Figure 6.8 summarises respondents' experiences with app functionality, the aspects of the Weather Risk app they liked most, and the functions or indices they perceived as most useful. Most respondents (60%) indicated that all app functions were working as expected, while 14% reported that some functions were not working as expected (Figure 6.8a). A further 27% indicated that they did not test all available functions (Figure 6.8a). Feedback from respondents who experienced issues was largely related to data display and stability during the testing phase, including difficulties viewing the most recent observed data and challenges with certain temperature-related functions. These issues are consistent with the app being under active development at the time of testing and have been used to guide subsequent debugging and refinement.

Respondents highlighted several aspects of the Weather Risk app that they liked most (Figure 6.8b). Ease of use was the most frequently cited feature (46%), followed by the overall layout of the app (41%; Figure 6.8b). Design and presentation, as well as the colour schemes used, were each highlighted by 23% of respondents (Figure 6.8b). These results indicate that the general structure and visual design of the app were well received, supporting earlier findings related to ease of navigation and interpretability.

In terms of perceived usefulness of specific functions or indices, rainfall-related indices were most frequently identified as useful (59%), followed by low-temperature indices (27%) and temperature indices more broadly (18%; Figure 6.8c). Among app features, the forecast slider and weather forecast functionality were each identified by 5% of respondents (Figure 6.8c). These results suggest that users place value on information related to rainfall and temperature extremes, reinforcing the importance of these components within the Weather Risk app for agricultural decision-making.

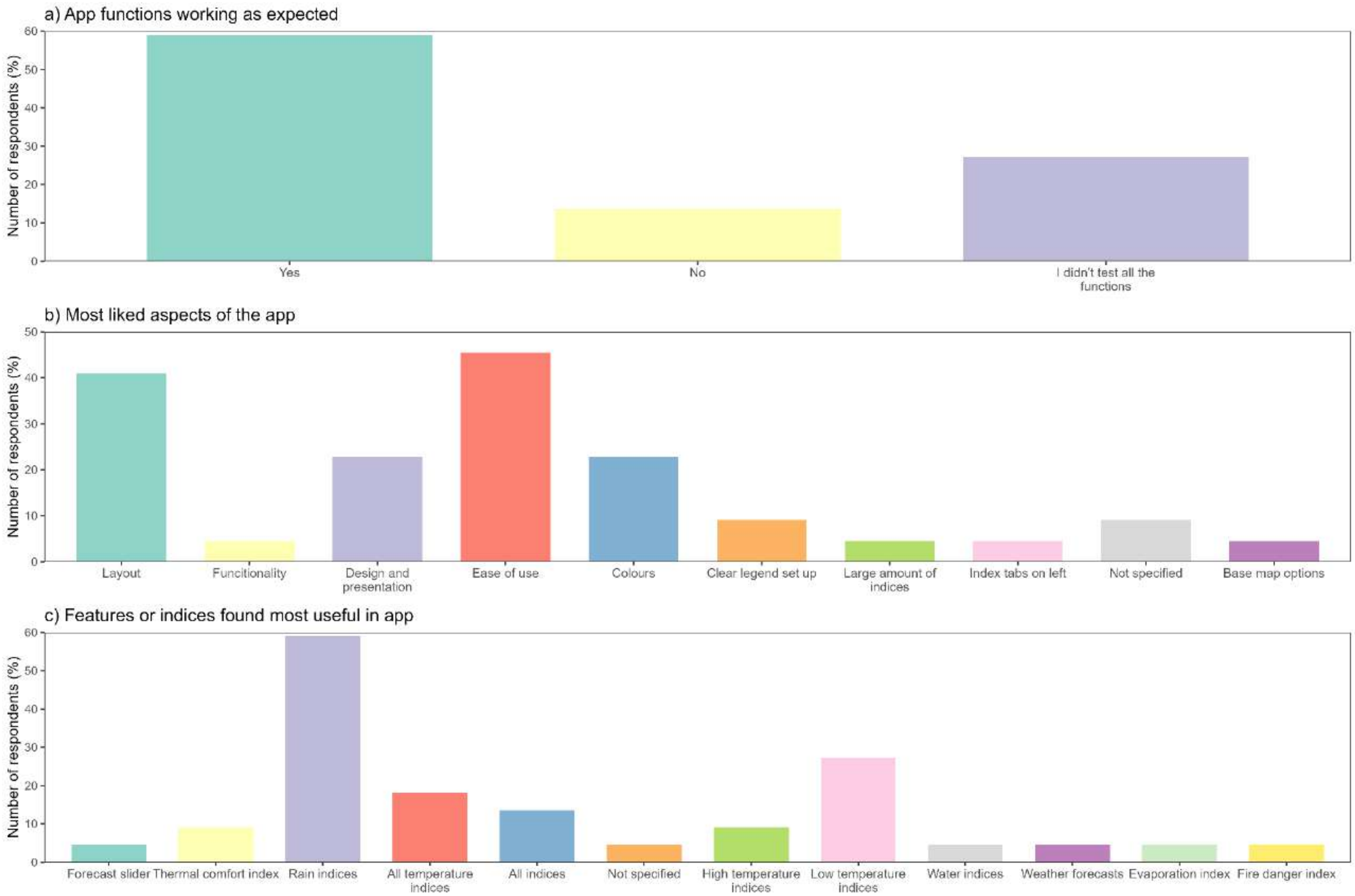

Figure 6.8: Responses showing a) whether the functions of the Weather Risk app work as expected, b) the aspects of the app most liked by respondents, and c) the functions or indices perceived as most useful within the app.

6.3.4 Relevance to work and decision-making potential

Figure 6.9 illustrates respondents' perceptions of how well the Weather Risk app aligns with their work or the work of those they support, as well as its perceived usefulness and potential for uptake. Most respondents (82%) indicated that the information provided by the app aligns well with their work or support role, while a further 18% indicated that it aligns somewhat (Figure 6.9a). This strong alignment suggests that the indices and information presented are broadly relevant to the professional and decision-making contexts represented within the stakeholder group.

Respondents also expressed a high likelihood of using or recommending the Weather Risk app, with 91% indicating that they would do so (Figure 6.9b). Reasons provided emphasised the accessibility of weather and climate information, the ease of use of the app, and the value of having multiple relevant indices packaged together within a single platform. Respondents highlighted the usefulness of the app for planning activities such as planting, spraying, field operations, and managing risks related to rainfall, temperature extremes, and frost, as well as its potential value for advising farmers, colleagues, and clients. Several respondents specifically noted the importance of forecasts and short-term summaries for improving planning and mitigating potential impacts.

Figure 6.9c further illustrates the range of decisions that respondents felt the Weather Risk app could support. The most frequently identified applications included planning planting or harvesting times (82%), timing pesticide or herbicide applications (77%), irrigation scheduling or water-use planning (77%), and advising colleagues, clients, or farmers (77%; Figure 6.9c). Consistent with this, perceptions of overall usefulness were strongly positive, with 36% of respondents indicating that the app would be extremely useful and 91% indicating that it would be at least moderately useful (Figure 6.9d). Feedback from respondents who rated usefulness as only slight highlighted a desire for additional features, such as subscription-based advisory messages (e.g., via SMS, email, or WhatsApp) and more explanatory information accompanying the data and forecasts. While these features were not yet implemented at the time of testing, they have been identified as priorities for future development of the Weather Risk app.

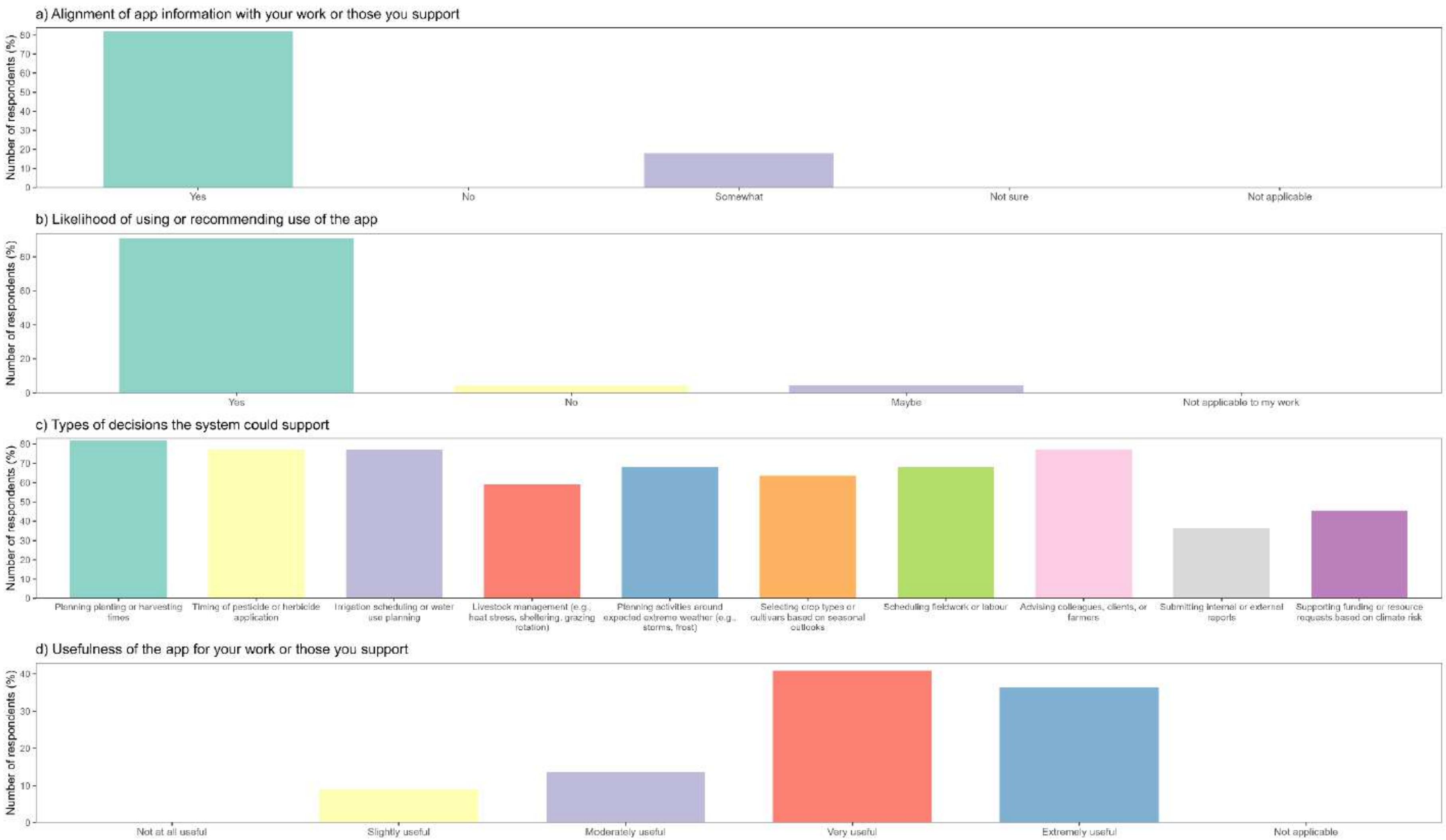

Figure 6.9: Responses showing a) the alignment of the app information with respondents' work or the work of those they support, b) the likelihood of using or recommending the Weather Risk app, c) the types of decisions the Weather Risk app could support, and d) the perceived usefulness of the app for respondents' work or the work of those they support.

6.3.5 Perceived impact, risk reduction, and recommended users

Figure 6.10 summarises respondents' views on the potential of the Weather Risk app to reduce risk and improve planning, the types of decisions it could support, willingness to recommend the system, and the intended user groups. Most respondents (73%) indicated that the system could help reduce risk and improve planning for their work or the work of those they support, while a further 27% indicated that it could possibly do so (Figure 6.10a). Qualitative feedback highlighted the value of the app for short-term and near-real-time planning, ease of access to multiple indices, and improved understanding of rapidly changing weather conditions. Respondents noted potential applications including planning planting dates, managing field activities, validating weather station data, supporting research, and assisting risk planners. Several respondents also emphasised that the system is particularly well-suited to short-term decision-making, with its usefulness increasing further if extended forecasts, daily updates, and more actionable advisory messages are incorporated in future versions.

Respondents identified a range of ways in which the Weather Risk app could support weather- and climate-informed decision-making (Figure 6.10b). The most frequently cited applications included planning various farming activities (46%), fieldwork scheduling (23%), implementation of pesticide and herbicide spray programmes (14%), planning crop types and planting or harvesting times (14%), and the potential value of push notifications or alerts if implemented (14%; Figure 6.10b). These responses reinforce the importance of actionable, timely information that directly supports operational and management decisions within agricultural systems.

Willingness to recommend the Weather Risk app was very high, with 96% of respondents indicating that they would recommend the system to others and a further 5% indicating that they might do so (Figure 6.10c). Reasons provided centred on the ease of use of the app, the accessibility of relevant weather information, and its value for planning and decision-making across a range of agricultural and research contexts. Respondents also highlighted the importance of mobile-friendly access and advisory messaging to further enhance uptake. In terms of intended users, respondents most frequently identified farmers (68%), followed by field officers (46%), extension officers (41%), agricultural policymakers and government organisations (23%), and researchers (14%; Figure 6.10d), indicating that the Weather Risk app has relevance across multiple levels of agricultural decision-making and support.

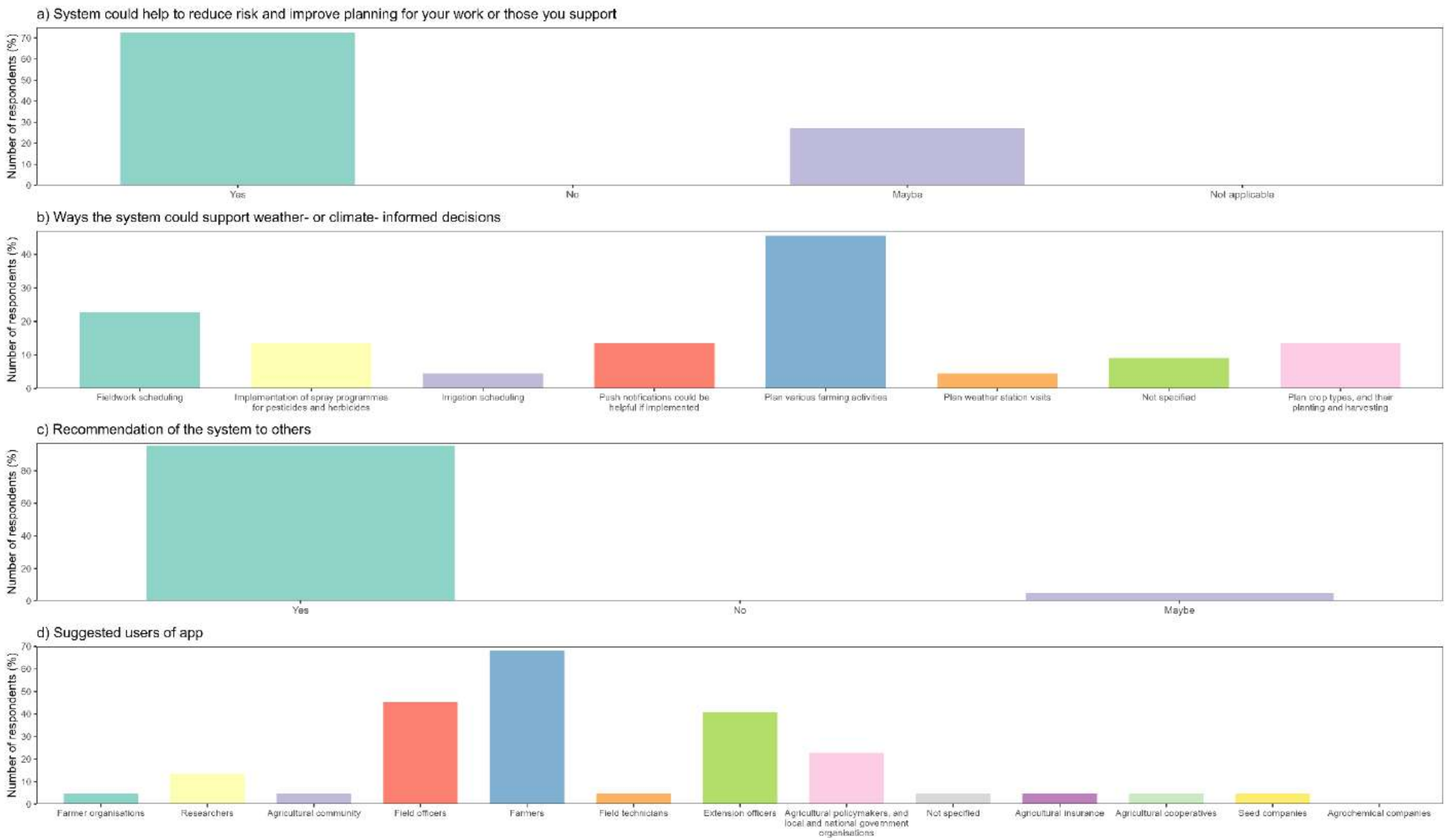

Figure 6.10: Responses showing a) whether the Weather Risk app could help reduce risk and improve planning for respondents' work or the work of those they support, b) the ways in which the Weather Risk app could support weather- or climate-informed decision-making, c) whether respondents would recommend the Weather Risk app to others, and d) the types of users to whom the app should be recommended.

Figure 6.11 summarises respondents' views on whether there were indices or information they expected to find in the Weather Risk app but did not, and whether additional content should be added. Just over half of respondents (55%) indicated that there were indices or information they expected but did not find, while 32% indicated that there were not, and 14% were unsure (Figure 6.11a). Responses highlighted a broad range of suggested additions, with recurring themes including soil-related information (e.g., soil moisture, soil water deficit, grazing capacity), atmospheric variables (e.g., humidity, leaf wetness, radiation, evaporation), and hazard-related information such as hail or windstorm warnings. Several respondents also expressed interest in compound or composite indices (e.g., combinations of temperature and humidity), vegetation indices, and drought-related indicators, as well as access to longer-term historical data alongside short-term information. In addition to new indices, respondents identified several functional and usability-related enhancements. These included the ability to view graphs or time series for selected locations, improved search functionality for towns or provinces, more flexible and intuitive date selection (including access to previous years), clearer legends and colour interpretation, and refinements to the forecast slider. Several respondents also emphasised the value of advisory or warning messages, mobile-friendly access, and more actionable guidance linked to the displayed indices. These suggestions reinforce feedback from earlier figures, indicating that users value not only access to data, but also clear interpretation and decision-relevant messaging.

Consistent with these findings, most respondents (77%) indicated that additional content or functionality should be added to the system, while 14% felt no additions were needed and 9% were unsure (Figure 6.11b). Importantly, the wide range of suggested additions reflects the diversity of user needs and decision contexts rather than a lack of perceived usefulness of the existing system. The feedback captured in Figure 6.11 has been used, together with insights from previous questions, to inform prioritisation of future development pathways for the Weather Risk app, including expansion of indices, enhanced visualisation options, and the integration of advisory-based features.

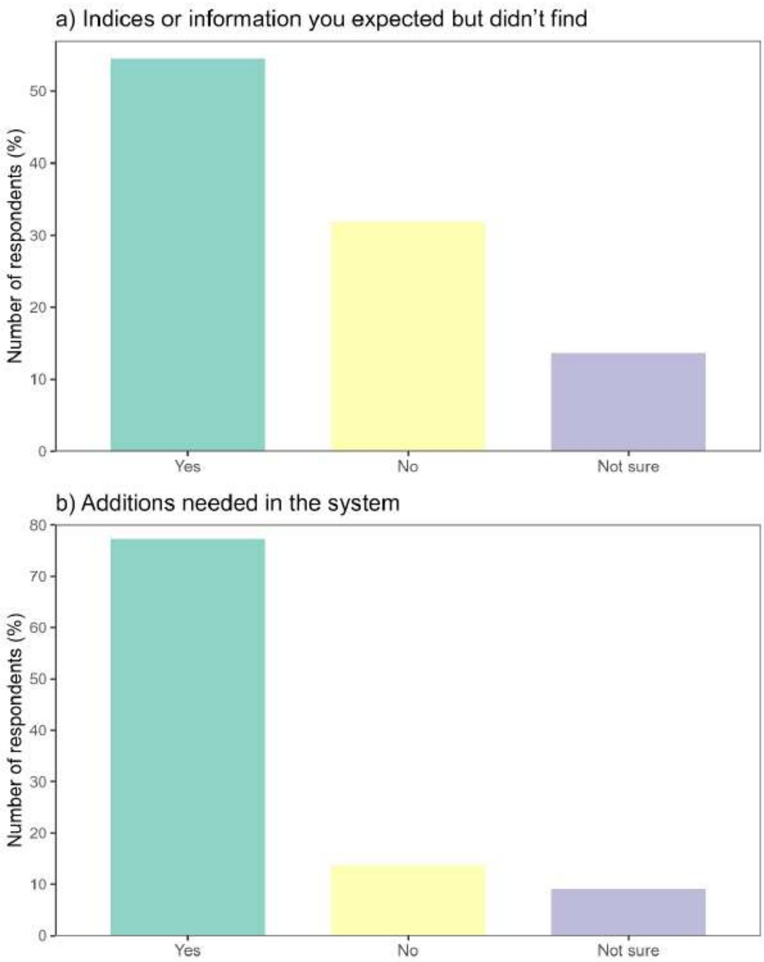

Figure 6.11: Responses to a) indices or info expected but didn't find, and b) suggested additions to the system.

6.4 Conclusions

This chapter demonstrated the value of active stakeholder engagement in assessing the usability, relevance, and practical applicability of the Weather Risk app prior to public release. Feedback from participants indicated strong alignment between the information provided by the app and the needs of users involved in agricultural decision-making or in supporting farmers and other stakeholders. Overall perceptions of usability, clarity, and usefulness were positive, with respondents highlighting the accessibility of weather and water availability information, the integration of multiple indices within a single platform, and the potential of the system to support short-term planning and risk reduction.

Importantly, stakeholder feedback also provided clear and constructive guidance on areas for improvement, including the need for clearer explanations, more intuitive legends and date handling, additional indices, and the integration of advisory-style features. These insights have already informed ongoing refinements to the Weather Risk app and will continue to guide future development priorities. The results presented in this chapter underscore the importance of user-centred design and iterative stakeholder engagement in enhancing the likelihood of adoption and sustained use of digital climate services, and position the Weather Risk app as a promising tool to support more proactive, weather-informed agricultural decision-making in South Africa.

Chapter 7: Synthesis and key insights

7.1 Project synthesis and delivery against objectives

The overarching aim of this project was to support agricultural decision-making in South Africa by identifying, testing, and operationalising selected weather- and climate-based indices through the development of an accessible, web-based climate and water availability information platform, namely the Weather Risk app. This chapter synthesises how this aim was achieved across the three project objectives, with emphasis on outcomes and contributions rather than on individual activities.

The first objective, which focused on a targeted review of climate databank applications, climate service principles, and commonly used weather-, climate-, and water-availability indices, was addressed comprehensively in Chapter 2. That review established a clear scientific and operational foundation for the project by identifying indices that are widely applied in South Africa, computationally feasible at the national scale, and relevant to weather- and climate-sensitive activities such as agriculture and water resource management. Importantly, the review was not intended to be exhaustive, but rather to provide a defensible and application-oriented inventory of indices that could realistically be operationalised. In parallel, the review of existing web-based climate applications and WCS principles situated the Weather Risk app within the broader landscape of operational WCSs, highlighting key requirements related to credibility, usability, transparency, and user-centred design.

The second objective was addressed through a series of illustrative case studies presented in Chapter 3, which evaluated selected gridded climate datasets and demonstrated the computation and application of rainfall- and temperature-based indices across different contexts. These case studies deliberately spanned both indices linked to agricultural indicators (e.g., crop production and livestock dynamics) and indices used to characterise climate extremes (e.g., heavy rainfall and extreme cold events). Collectively, they demonstrated how indices behave across datasets, regions, and time scales, while explicitly highlighting sources of uncertainty, dataset-specific biases, and context-dependent relationships. Rather than seeking to establish definitive causal links between climate indices and agricultural outcomes, these analyses illustrated both the potential value and the limitations of indices as interpretative tools.

The third objective, namely the development and implementation of a web-based application providing spatially explicit weather-based indices alongside selected water availability indicators, was addressed through Chapters 4, 5, and 6. Stakeholder consultations and questionnaire responses informed the user-centred design of the Weather Risk app, ensuring that index selection, presentation, and functionality aligned with user needs and expectations. The subsequent development and testing of the platform demonstrated how indices reviewed and evaluated earlier in the project could be operationalised in a way that lowers technical barriers to access while retaining scientific transparency.

Taken together, the project successfully delivered an integrated workflow that moves from review and evaluation to application and operationalisation. The Weather Risk app represents the culmination of this process, providing a practical mechanism through which selected weather and water availability indices can be accessed and interpreted within an agricultural decision-making context. In doing so, the project achieved its stated aim while remaining explicit about the scope, strengths, and limitations of indices as decision-support information.

In this context, the project prioritised the demonstration and operationalisation of selected weather- and climate-based indices through an accessible, web-based platform, rather than the full validation of all indices ultimately implemented in the Weather Risk app. Detailed evaluation was undertaken for selected datasets and indices to illustrate their application, behaviour, and limitations, while the app itself incorporates a broader set of weather-based and water availability indices based on established practice, data availability, and relevance to agricultural stakeholders.

7.2 Key scientific and applied insights

Several cross-cutting scientific and applied insights emerge from the combined findings of the dataset evaluations, index applications, and case studies presented in this report. A central insight is that weather and climate indices are most informative when they capture cumulative conditions, persistence, and threshold exceedances, rather than relying solely on mean values. Across rainfall and temperature analyses, indices describing seasonality, frequency of extremes, and duration of anomalous conditions consistently provided richer context than simple averages.

The case studies further highlighted that index behaviour is strongly context dependent. Relationships between indices and agricultural indicators varied by region, production system, season, and time scale. For example, temperature- and heat-related indices showed differing relevance for livestock versus crop systems, while rainfall indices exhibited variable associations depending on seasonal timing and rainfall regime. These findings reinforce that indices cannot be interpreted uniformly across South Africa and must be considered within their local climatic, environmental, and management context.

Evaluation of gridded datasets revealed that while many indices show consistent large-scale spatial and temporal patterns across products, important differences remain in magnitude, bias, and variability. These differences are particularly evident for extreme rainfall and cold temperature indices, where dataset resolution, input observations, and methodological choices influence outcomes. The project, therefore, underscores the importance of dataset evaluation as a prerequisite for operational index use, particularly when indices are intended for monitoring or comparative assessment.

A further insight relates to uncertainty. Across all case studies, uncertainty arises not only from data limitations but also from methodological decisions, including threshold definitions, aggregation periods, and index formulations. Rather than viewing this as a weakness, the project demonstrates that transparent communication of uncertainty is essential for responsible index use. Indices are best understood as indicators of conditions and potential risk, rather than as precise predictors of agricultural outcomes.

7.3 Value, limitations, and appropriate use of weather and climate indices in agriculture

The findings of this project confirm that weather and climate indices provide substantial value for agricultural awareness, monitoring, and contextual interpretation of conditions. By translating complex daily weather and climate data into interpretable metrics, indices offer a practical means of linking atmospheric conditions to weather- and climate-sensitive activities. For agricultural users, indices describing rainfall persistence, heat stress, frost occurrence, or recent anomalies are often more intuitive and actionable than raw meteorological variables.

Indices are particularly valuable for situational awareness, retrospective assessment, and comparison of current conditions against historical baselines. When applied consistently across space and time, they allow users to identify periods of heightened stress, emerging risks, or unusual conditions that may warrant closer attention. In this sense, indices support informed interpretation rather than direct decision-making.

At the same time, the project clearly demonstrates important limitations. Indices necessarily simplify complex processes and do not account for non-climatic drivers such as management practices, market conditions, or institutional constraints. Their interpretation is sensitive to data quality, spatial resolution, temporal aggregation, and threshold selection. Moreover, indices derived from gridded datasets may not capture local-scale variability experienced at the farm level.

Appropriate use of weather and climate indices, therefore, requires caution and contextual understanding. Indices should be interpreted as indicative rather than deterministic, and preferably used in combination rather than in isolation. Clear guidance on what each index represents, its underlying data sources, and its limitations is essential to avoid misinterpretation. The project reinforces the importance of framing indices as part of a broader evidence base that can support, but not replace, expert judgement and local knowledge.

7.4 Operational value of the Weather Risk app for agricultural decision-making

The Weather Risk app provides spatially explicit weather-based indices, alongside selected water availability indicators, through an interface designed to be accessible to a diverse range of agricultural stakeholders. In doing so, it functions as an operational WCS that seeks to improve access to, and interpretation of, weather- and climate-related information relevant to agriculture in South Africa. The Weather Risk app was made available to the wider public, beyond the ARC network, in December 2025. This marked the transition of the platform from an internal development and testing environment to an operational WCS with open public access. From February 2026, the platform will be actively publicised through broader communication and outreach activities, including social media channels, to increase visibility and uptake among agricultural stakeholders.

Given the timing of its public release, the Weather Risk app should be viewed as an operational service that is still in an active phase of testing, refinement, and enhancement. While core functionality and a substantial suite of indices are currently available, ongoing development is expected as user feedback is incorporated, additional features are implemented, and data inputs and indices are refined or expanded where feasible. This iterative approach is consistent with standard practice in the delivery of operational WCSs.

Stakeholder engagement and user testing undertaken during the project indicate that the platform's emphasis on indices, rather than raw data, enhances interpretability and relevance. Users valued the ability to visualise recent and historical conditions, explore spatial patterns, and compare different indicators across South Africa. The inclusion of both weather-based and selected water availability indicators enables users to contextualise atmospheric conditions within a broader resource-management framework, even at this early stage of public availability.

The operational value of the Weather Risk app lies not in prescribing decisions, but in supporting informed awareness, situational assessment, and planning. By lowering technical barriers and providing transparent, well-documented indices, the platform enables users to engage more effectively with weather and climate information, while recognising that continued testing, maintenance, and enhancement will extend beyond the lifespan of the current project.

7.5 Lessons learned, recommendations, and concluding synthesis

Several key lessons emerge from this project regarding the development and delivery of operational WCSs for agriculture. One of the most important lessons is the need to clearly distinguish between scientific evaluation and operational implementation. While rigorous evaluation of datasets and indices is essential for building credibility and understanding limitations, operational services must also balance completeness, usability, and feasibility. In this project, evaluation was undertaken for selected weather- and climate-based indices and datasets to demonstrate their application, behaviour, and limitations, while the Weather Risk app operationalises a broader set of weather-based and water availability indices to support practical interpretation and user engagement.

A second key lesson relates to the central role of user-centred design and stakeholder engagement. Engagement activities conducted throughout the project demonstrated that agricultural users value information that is accessible, spatially explicit, and framed in terms of indices rather than raw data. Feedback from these activities directly informed the design, functionality, and presentation of the Weather Risk app, reinforcing the importance of iterative engagement in ensuring relevance and usability. This lesson highlights that effective WCSs are not static products, but evolving systems shaped through ongoing interaction between developers and users.

The project also underscores the importance of transparency around uncertainty and limitations. Weather- and climate-based indices simplify complex physical processes and are sensitive to data quality, methodological choices, and spatial and temporal scale. Clear communication of these limitations is essential to support appropriate interpretation and to avoid overconfidence in index outputs, particularly within an operational service that may inform agricultural planning and risk awareness. This transparency is a critical component of building trust in WCSs.

Building on these lessons, several priority recommendations for future research, data development, and platform enhancement are identified. From a research perspective, further work is needed to strengthen the understanding of how weather- and climate-based indices relate to agricultural responses across different production systems, regions, and time scales. While this project demonstrated the application and behaviour of selected indices, future research would benefit from more systematic investigation of index-impact relationships, including compound and interacting risks such as hot-dry conditions, heat stress combined with limited water availability, and the co-occurrence of multiple weather extremes. Further research examining the links and interactions between weather-based indices and water availability indices would also add value, enabling a more integrated understanding of climate and hydrological drivers of agricultural risk.

Continued evaluation of datasets represents a further priority. Differences identified between gridded products, particularly for extreme rainfall and cold temperature indices, highlight the need for ongoing benchmarking as updated gridded data products become available. Future work should prioritise systematic comparison against observations, improved characterisation of uncertainty, and assessment of dataset suitability for operational index calculation. This is especially important as operational platforms increasingly rely on gridded datasets to provide spatially complete and temporally consistent information.

Future research should also focus on strengthening forecasting capabilities within the Weather Risk app. The integration and refinement of short- to medium-range forecasts, together with the development of forecast-based indices and indicators, represents a major opportunity to enhance the platform's operational value. Improved forecasting functionality would support anticipatory planning and risk preparedness, and is likely to be a key strength of the Weather Risk app as it continues to develop. Continued investment in forecast evaluation, bias assessment, and communication of forecast uncertainty will therefore be essential.

In terms of data development, expanding and strengthening the representation of water availability within the Weather Risk app represents a key opportunity. While the current platform includes selected water availability indices, future phases could focus on improving temporal resolution, incorporating additional hydrological variables, and strengthening linkages between atmospheric conditions and water resource responses. Such developments would enhance the platform's relevance for irrigated agriculture and water resource management, particularly under increasing climate variability and growing competition for water.

With respect to platform enhancement, the Weather Risk app should be viewed as a foundational system that requires sustained development, maintenance, and evaluation beyond the lifespan of the current project. Future enhancements may include the addition of new weather-based and water availability indices, improved functionality and customisation options, expanded interpretive guidance, and strengthened mechanisms for user feedback and co-development. As user uptake increases, formal evaluation of how the platform is used within different decision contexts will become increasingly important to guide targeted improvements and demonstrate impact.

In conclusion, this project has demonstrated the value of weather- and climate-based indices for interpreting and contextualising agricultural risk, while also highlighting the practical considerations involved in delivering such information through an operational service. By integrating targeted review, applied evaluation, stakeholder engagement, and the development of a publicly accessible WCS, the project provides a robust foundation for the continued evolution of the Weather Risk app. The outcomes of this work represent both a proof of concept and a strong platform for future investment aimed at advancing operational WCSs to support agricultural resilience and climate risk awareness in South Africa.

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Appendices

Appendix 1: Capacity building across the project

A1.1 Project team capacity building

Several project team members were, and continue to be, capacitated through this project. This includes early-career researchers such as Dr S Roffe, Dr R Rapolaki, Dr L Myeni, and Dr A van der Walt. Key growth has come through supervising postgraduate students, strengthening their academic mentorship and research leadership.

Additional capacity building occurred through project management responsibilities. Dr S Roffe served as project leader for the first time, gaining experience in research leadership, coordination, and reporting.

A1.2 Postgraduate student capacity building

Several Doctoral and Master's students have been capacitated through this project. The following students are, or were, registered under this project ('status' reflects the status of studies upon the completion of the project):

Student: Ms Dimakatso Ndaleni

Institution: Department of Geography, University of the Free State

Topic: Evaluating the performance of ERA5-based reanalysis products in representing rainfall indices across South Africa

Level: MSc

Supervisors: Dr S Roffe, Dr R Rapolaki and Dr A van der Walt

Status: Ongoing

Student: Mr Munei Mugeri

Institution: Department of Geography, University of the Free State

Topic: Variability in the Evaporation – Precipitation relationship and associated moisture transport in the Vaal Water Management area, South Africa

Level: MSc

Supervisors: Dr R Rapolaki, Dr S Roffe and Dr A van der Walt

Status: Ongoing

Student: Ms Namhla Mkiva

Institution: Department of Geography and Environmental Studies, North West University

Topic: Assessing climate change impacts on crop water availability and formulating responsive adaptation strategies in the Marico catchment, North West Province

Level: PhD

Supervisors: Dr L Myeni, Dr S Roffe and Dr M van der Laan

Status: Ongoing

Student: Mr Ngwako Mohale

Institution: Department of Geography, University of the Free State

Topic: Identification and characterisation of extreme low temperature events over the Limpopo River Basin, southern Africa

Level: MSc

Supervisors: Dr S Roffe, Dr R Rapolaki and Dr A van der Walt

Status: Complete

Student: Ms Nicolle Loader

Institution: Department of Geography, University of the Free State

Topic: Above-normal summer temperatures in South Africa: indices, reanalysis evaluation, and links to the Botswana High and ENSO

Level: MSc

Supervisors: Dr S Roffe, Dr R Rapolaki and Dr A van der Walt

Status: Ongoing

Appendix 2: Research Dissemination

A2.1 Conference attendance across the project

During the lifetime of the project, the research team, including researchers, a postdoctoral fellow, and postgraduate students, actively participated in several scientific conferences, delivering a total of 15 oral and poster presentations (Table A2.1). Apart from the international conferences attended by Dr C Viviers in Istanbul, Turkey and Dr L Myeni in Windhoek, Namibia, all other events were national conferences held in South Africa.

The national conferences were particularly valuable as they provided opportunities to engage directly with potential users of the Weather Risk app. Notably, oral presentations by Dr S Roffe at the Water Institute of Southern Africa (WISA) Biennial Conference and the Combined Congress, as well as her poster presentation at the South African Society for Atmospheric Sciences (SASAS) Annual Conference, highlighted the project's innovative approach to integrating weather and water data into the Weather Risk app to support agricultural decision-making. These presentations also demonstrated the project's co-development process, emphasising collaboration between researchers, developers, and sectoral stakeholders.

Participation in other national forums, including the Society of South African Geographers (SSAG) Biennial Conference, the Southern African Mountain Conference, and the Agroclimate Symposium, allowed postgraduate students involved in the project to present their research on topics such as cold temperature and rainfall indices, atmospheric circulation patterns, and data evaluation methods. These platforms provided valuable exposure for the students and strengthened the overall visibility of the project within the broader climate and agricultural research community.

Table A2.1: Conference attendance details throughout the project (April 2023 to March 2026).

Presentation title (type of presentation: oral or poster)	Author(s) (Presenting author is listed in bold)	Name of conference	Location of conference	Dates of conference
Developing a web-based app with hydrometeorological indices to support decision-making across South Africa (oral)	**Roffe S**, Malherbe J, Beukes P, Rapolaki R, Myeni L, van der Laan M, Viviers C, van der Walt A, De Nysschen G, Masupha T, Moeletsi M	WISA 2024 Biennial Conference & Exhibition	Durban, South Africa	12-14 June 2024
Assessment of users' needs for weather and climate information in the South African water sector (oral)	Myeni L, **Roffe S**	WISA 2024 Biennial Conference & Exhibition	Durban, South Africa	12-14 June 2024
A WRF simulation of the July 2023 snowfall event over South Africa (oral)	**Singo M**, Roffe S, Malherbe J	WISA 2024 Biennial Conference & Exhibition	Durban, South Africa	12-14 June 2024
Characterising extreme cold events in the Limpopo River Basin, southern Africa: 1979-2021 (oral)	**Mohale N**, Roffe S, van der Walt A, Rapolaki R	2024 SSAG Biennial conference	Potchefstroom, South Africa	16-18 September 2024
Evaluation of ERA5-based reanalysis products for the representation of cold extreme temperature indices over southern Africa (oral)	**Roffe S**, Singo M	2024 SSAG Biennial conference	Potchefstroom, South Africa	16-18 September 2024
Spatiotemporal analysis of heavy summer rainfall events across the Free State Province, South Africa: 1981–2022 (oral)	**Loader N**, Roffe S, van der Walt A	International Higher Education Teaching and Learning Association Conference	Gqwberha, South Africa	2-4 October 2024
Using remotely sensed imagery to track irrigation for sustainable groundwater management (oral)	**Viviers C**, van der Laan M	Sustain Istanbul 2024: Towards Sustainable Groundwater Use under Changing Climate	Istanbul, Turkey	9-11 October 2024
Assessment of users' needs for weather and climate services in the	Myeni L, **Roffe S**	Combined Congress 2025	Polokwane, South Africa	19-24 January 2025

South African agriculture industry (oral)				
Assessing the data quality of ERA5 datasets in relation to summer temperature indices over South Africa: 1979-2023 (oral)	**Loader N**, Roffe S, Rapolaki R, van der Walt A	2nd Southern African Mountain Conference	Drakensburg, South Africa	17-20 March 2025
Validating soil moisture and temperature forecasts to strengthen climate-resilient agriculture in South Africa (poster)	**Myeni L**, Roffe S, Malele P	Agroclimate symposium	Roodeplaat, South Africa	9-10 September 2025
Characterising Extreme Low Temperature Events and associated atmospheric circulations in the Limpopo River Basin (poster)	**Mohale N**, Roffe S, Rapolaki R, van der Walt A	Agroclimate symposium	Roodeplaat, South Africa	9-10 September 2025
Climatological analysis of Evaporation minus Precipitation variability in the Vaal Water Management Area, South Africa: 1980-2023 (poster)	**Mugeri ME**, Roffe S, van der Walt A, Rapolaki R	Agroclimate symposium	Roodeplaat, South Africa	9-10 September 2025
Ongoing validation of soil moisture and temperature forecasts for agricultural management in South Africa (poster)	**Myeni L**, Roffe S	Climate Change and Futures in Africa Conference Series 2025	Windhoek, Namibia	29-31 October 2025
Characterising Extreme Low Temperature Events and associated atmospheric circulations in the Limpopo River Basin (oral)	**Mohale N**, Roffe S, Rapolaki R, van der Walt A	39th Annual Conference for the SASAS	Cape Town, South Africa	13-14 November 2025
Farmer-focused weather risks: a web app for agricultural weather and water insights in South Africa (poster)	**Roffe S**, Malherbe J, Beukes P, Viviers C, van der Laan M, Rapolaki R, Myeni L, van der Walt A, De Nysschen G, Masupha T, Moeletsi M	39th Annual Conference for the SASAS	Cape Town, South Africa	13-14 November 2025

A2.2 Scientific publications: completed and forthcoming

To date, the project team has produced four publications, with several additional papers in various stages of development (Table A2.2). The first publication, a public media article, published with Stockfarm and authored by Dr S Roffe, highlights the importance of using climatic indices to inform agricultural decision-making. The second, co-authored by Dr S Roffe and Mr M Singo, focuses on cold temperature indices, providing both a review of existing indices and an evaluation of the accuracy of ERA5-based gridded datasets in representing these indices. This work was published in the SSAG Conference Proceedings. The third publication, co-authored by Dr L Myeni and Dr S Roffe, examines stakeholder engagement processes and was published in the journal Environmental Development. A fourth publication, authored by Dr S Roffe, summarised the results of this stakeholder engagement study, focusing specifically on findings relevant to the agricultural sector. This was published in AgriAbout magazine.

Looking ahead, one manuscript has been submitted by Mr M Singo, Dr S Roffe and Dr J Malherbe for peer review to the journal Natural Hazards, providing an evaluation of the ARC forecast's performance in simulating conditions associated with a major snowfall event. This analysis also serves as an assessment of the forecast configuration used to produce data for the Weather Risk app. In addition, two further manuscripts are currently in preparation for submission to peer-reviewed journals. The first will be based on the MSc research completed by Mr Ngwako Mohale, focusing on extreme low-temperature events in the Limpopo River Basin. The second will be led by Dr S Roffe and includes the project team, and will describe the development, structure, and functionality of the Weather Risk app in full.

Beyond these, several MSc and PhD students involved in the project are expected to produce publications from their research. Ms Dimakatso Ndaleni aims to publish on the reliability of ERA5-based rainfall datasets in representing rainfall indices, while Ms N. Loader aims to prepare two manuscripts, one on warm temperature indices and another examining the influence of the Botswana High Pressure System on the variability of warm temperature indices during the summer season. Mr Munei Mugeri aims to develop publications on freshwater flux variability over the Vaal Water Management Area, considering both interannual and climatological scales, and associated moisture transport processes. Ms Namhla Mkiva aims to publish from her PhD work, which focuses on assessing climate change impacts on crop water availability and formulating responsive adaptation strategies in the Marico Catchment, North West Province.

Overall, by the end of the two years (i.e., March 2028) following the project, the team is expected to have produced more than ten peer-reviewed and applied publications arising directly from this research. This strong publication output aligns with the project's objectives of promoting scientific excellence, advancing knowledge on climate-agriculture linkages, and ensuring wide dissemination of results. Collectively, these outputs will make the project one of the most comprehensively published initiatives within its field.

Table A2.2: Scientific publication details throughout the project (April 2023 to March 2026).

Article title	Author(s)	Journal, Conference proceeding or Newsletter	Status (In preparation; Submitted; Under revision; In press; Published)	DOI (for in press and published journal articles) or link to article
Climate indices for informed agricultural decision-making	Roffe S	Stockfarm	Published	https://agriorbit.com/climate-indices-for-informed-agricultural-decision-making/
Evaluation of ERA5-based reanalysis products for the representation of cold extreme temperature indices over southern Africa	Roffe S, Singo M	Society of South African Geographers Biennial Conference Proceedings	Published	https://www.ssag.co.za/wp-content/uploads/2024/11/SSAG_2024_Proceedings.pdf
Towards effective weather and climate services in South Africa: profiling sectoral needs and constraints	Myeni L, Roffe S	Environmental Development	Published	https://doi.org/10.1016/j.envdev.2025.101240
Shaping South Africa's weather and climate services – together for agriculture	Roffe S	AgriAbout	Published	https://heyzine.com/flip-book/0d675fc05b.html
A WRF simulation of the July 2023 snowfall event over South Africa	Singo M, Roffe S, Malherbe J	Meteorology and Atmospheric Physics	Under revision	-
Observed trends and synoptic drivers of extreme low temperature events in the Limpopo River Basin: 1979–2021	Mohale N, Roffe S, van der Walt A, Rapolaki R	Target journal: Theoretical and Applied Climatology	In preparation	-
From data to decision support: the Weather Risk App for agriculturally relevant weather and water availability insights in South Africa	Roffe S, Malherbe J, Beukes P, Viviers C, van der Laan M, Rapolaki R, Myeni L, van der Walt A, De Nysschen G, Masupha T, Moeletsi M	Target journal: Computers and Electronics in Agriculture	In preparation	-