

Crop suitability, yield volatility and loss distribution shifts under climate change: an actuarial modelling framework

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ABSTRACT

Agricultural production is closely linked to climate variability and weather extremes, making it particularly vulnerable to changing weather patterns and the increasing frequency of extreme events associated with climate change. Historical yield statistics provide limited information on the underlying climatic and environmental drivers influencing agricultural crop performance. This study examines these relationships for maize and wheat production in the Free State, South Africa, by combining climate, hazard, vegetation and crop suitability data into an integrated geospatial framework.

Climate reanalysis, the Oceanic Niño Index, Normalised Difference Vegetation Index (NDVI), agricultural production areas and land cover data were analysed using crop-specific growing seasons for summer maize and winter wheat. Seasonal rainfall and temperature were considered alongside drought, heatwave, extreme rainfall and fire-weather conditions. Climatic suitability was estimated using crop-specific Food and Agriculture Organization requirements and adjusted using seasonal hazard penalties to account for weather extremes occurring during the growing season.

Clear spatial and temporal differences were observed across the Free State. Climatic suitability generally increased from the drier western areas towards the wetter eastern production regions, while the effect of hazard adjustment varied between seasons. NDVI also varied between years

and showed some correspondence with observed crop productivity, although this relationship differed between maize and wheat.

A hierarchical modelling approach, combining Principal Component Analysis and Ordinary Least Squares regression was used to test whether hazards, El Niño-Southern Oscillation (ENSO), vegetation, and suitability added information beyond seasonal climate variables. The results show that seasonal climate alone does not capture all of the variability associated with crop productivity. Including weather extremes, ENSO and observed vegetation response provides additional information on crop performance. Beyond traditional crop monitoring, the methodology provides a scalable approach for identifying climate-sensitive agricultural regions and supporting applications in crop insurance, agricultural lending, climate risk stress testing and broader financial risk management.

KEYWORDS

Climate risk; agriculture; NDVI; remote sensing; ENSO; climate hazards; insurance; banking; South Africa

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1. INTRODUCTION

1.1 Agricultural production is shaped by the interaction of long-term climatic conditions, short-duration weather extremes, crop phenology, soil and water availability, management practices and market incentives. Climate change adds a persistent shift to this already variable system. The Intergovernmental Panel on Climate Change (IPCC) concludes that climate-related risks to food production and food security rise with increasing warming and that adaptation limits become more pronounced in vulnerable regions and production systems (IPCC, 2022; 2023).

1.2 These issues are especially relevant for Southern Africa, where rain-fed cereal production is exposed to high interannual rainfall variability, recurrent drought and heat stress. The region's agricultural risk is not adequately described by annual average climate alone. A season may receive near-normal total rainfall but still experience damaging dry spells, extreme heat during sensitive growth stages, excessive rainfall or delayed onset. Conversely, a below-average rainfall season may produce acceptable yields where rainfall timing, soil moisture retention, irrigation and management are favourable. This distinction between average suitability and realised seasonal stress motivates exploring an integrated approach that combines climatic conditions, hazards and direct observations of vegetation response.

1.3 From an actuarial and risk perspective, agricultural climate risk has direct implications for insurers, banks, investors, and the public sector. Lower production and greater yield volatility can increase indemnity claims, weaken farm income, reduce debt-servicing capacity and affect the value of agricultural collateral. These effects can transmit into higher probabilities of default, greater loss given default, portfolio concentration risk, and increased capital or provisioning requirements. They may also create correlated losses across geographically concentrated agricultural portfolios (Pozdyshev et al., 2025). A spatially integrated framework can support the assessment of climate risk and resilience by informing risk segmentation, client engagement, product design, climate risk-related stress testing, and regulatory requirements for financial institutions.

2. LITERATURE REVIEW

2.1 The literature supporting such integration is distributed across several fields. Climate-impact studies estimate yield responses to temperature and rainfall. El Niño-Southern Oscillation (ENSO) studies examine predictable modes of interannual variability. Remote-sensing studies derive vegetation condition and phenology. Crop-suitability models compare environmental conditions with biological requirements. Finally, statistical or machine-learning models identify relationships between predictors and yields. Each body of work is valuable, but the separation between them can produce fragmented risk assessments. This review therefore evaluates the evidence for combining these strands within one geospatial and crop-seasonal framework for maize and wheat in the Free State.

2.2 The ENSO is a fundamental driver of interannual crop variability globally (Iizumi et al., 2014) and historically serves as an important indicator for assessing regional crop vulnerabilities in Africa (Sazib et al., 2020; Singels & Bezuidenhout, 1999). Recent advancements demonstrate that integrating ENSO forecasting into climate reanalysis models can provide powerful, pre-season yield predictions for staple crops like maize and wheat, offering early warnings up to a year ahead of the harvest (Anderson et al., 2024).

2.3 Beyond interannual crop variability, underlying climate trends impose severe constraints on agricultural viability. Historical temperature trends have demonstrably reduced global maize and wheat production (Lobell et al., 2011), and multi-model projections show that further temperature increases will continue to depress these staple crop yields (Zhao et al., 2017). Extreme weather disasters – notably severe droughts and extreme heat – compound these gradual declines by causing acute, devastating shocks to national cereal production (Lesk et al., 2016). Consequently, modelling frameworks must account for the non-linear sensitivities of crops to these complex moisture and temperature extremes during critical developmental phases (Roberts et al., 2017). In Southern Africa specifically, mapping the realistic ecological niche of staple crops requires a hazard-adjusted suitability approach

that incorporates indices for extreme climate events (e.g., heatwaves and consecutive dry days) rather than relying solely on season-long climate averages (Chemura et al., 2022).

2.4 Earth observation (EO) technologies serve as the empirical bridge linking modelled climate hazards to physical crop responses. The Normalised Difference Vegetation Index (NDVI) is widely used in dryland and semi-arid African contexts as a robust proxy for vegetation productivity and green biomass (Tian et al., 2016). Highlighting a successful Southern African application, Mashaba et al. (2017) demonstrated that integrating NDVI data with meteorological parameters provides highly effective pre-harvest yield forecasting for winter wheat in the central Free State region of South Africa.

2.5 To leverage EO data effectively in climate-risk frameworks, raw satellite time-series must be refined to extract meaningful phenological markers (e.g., the onset, peak, and duration of the growing season). Foundational techniques, such as applying Savitzky-Golay filters to reconstruct high-quality NDVI time series (Chen et al., 2004), ensure that these NDVI-derived seasonal metrics accurately reflect true crop dynamics rather than atmospheric noise. This allows for the precise quantification of how crops physically respond to intra-seasonal climate shocks.

2.6 Combining climate reanalysis data, ENSO indices, hazard-adjusted suitability, and NDVI metrics inherently generates a high-dimensional feature space susceptible to redundancy and multicollinearity. In quantitative assessments of agricultural climate risk, dimensionality reduction techniques such as Principal Component Analysis (PCA) and Principal Component Regression (PCR) are utilised to resolve high-dimensional collinearity among climatic and environmental variables. Cai et al. (2011) demonstrated that constructing orthogonal weather components from correlated seasonal indicators effectively eliminates variance inflation while preserving the underlying structure of climate signals, yielding stable coefficient estimates across different ecological zones.

3. RESEARCH QUESTIONS

3.1 Climate risk and agriculture

3.1.1 Physical climate risk refers to the financial consequences arising from acute weather events and chronic climatic changes. Within agricultural systems these risks manifest through several mechanisms, including reduced soil moisture availability, elevated temperatures, increased evapotranspiration, flooding, wildfire occurrence and changing growing conditions.

3.1.2 Crop yields seldom respond to a single climatic variable in isolation. Instead, agricultural productivity reflects the cumulative interaction between rainfall distribution, temperature, soil conditions, vegetation health and the occurrence of extreme weather events throughout the growing season. Consequently, traditional analyses based

solely on annual rainfall or temperature often fail to capture the complexity of agricultural production systems.

3.1.3 Conventional agricultural assessments frequently rely on annual or provincial production and productivity statistics. These data are essential for measuring realised outcomes, but they provide limited information on the processes that produced those outcomes. Annual totals can conceal the timing of rainfall, the occurrence of damaging events within critical growth stages, spatial differences across production regions and the cumulative response of vegetation to environmental stress.

3.1.4 Productivity reflects the combined influence of various environmental factors mentioned above. These factors operate at different spatial and temporal resolutions. A central methodological challenge is to harmonise them into a common crop-season framework without losing their physical interpretation.

3.2 Financial and actuarial relevance

3.2.1 Changes in agricultural production and yield volatility create additional risks to financial institutions and the public sector. Actuaries and risk professionals in these areas need to quantify these risks and their impacts on portfolio concentration, credit metrics, underwriting standards and capital requirements.

3.2.2 Financial institutions and regulators increasingly require evidence-based approaches for identifying physical climate risk, assessing vulnerability and testing the resilience of portfolios under adverse conditions. For agricultural exposures, this requires methods that link physical conditions to observable production outcomes while remaining transparent enough for model governance, validation and stakeholder interpretation. A spatially explicit framework can also support risk segmentation, client engagement, index linked solutions (e.g., parametric products), insurance design, portfolio monitoring, and climate risk stress testing.

3.2.3 When financial institutions can accurately quantify and absorb climate-related agricultural risks, it directly bolsters the financial resilience of the farming sector. This could allow improved access to appropriately priced credit and insurance products to protect the livelihoods of both commercial and emerging smallholder farmers. This framework facilitates a more robust financial safety net, and in doing so, contributes to the preservation of rural employment, sustains local agricultural economies, and mitigates the societal impacts of an increasingly volatile climate.

3.3 Why the Free State?

3.3.1 The Free State represents one of South Africa's most important grain-producing regions and contributes substantially to national maize and wheat production. The province contains extensive commercial farming operations characterised by relatively homogeneous management practices and broad areas of rain-fed agriculture, making it particularly suitable for investigating climatic influences on crop production.

3.3.2 The province also exhibits considerable climatic variability. Summer rainfall dominates much of the region, while temperature gradients associated with elevation and continentality influence crop development across different production zones. Periodic droughts linked to ENSO events have historically resulted in substantial reductions in agricultural production, highlighting the sensitivity of regional farming systems to large-scale climate variability. The combination of significant agricultural production, diverse climatic conditions and extensive historical observations makes the province an ideal case study for developing an integrated agricultural climate risk framework.

3.4 Remote sensing and earth observation for agricultural monitoring

3.4.1 Satellite remote sensing has transformed agricultural monitoring by providing consistent observations of vegetation conditions across large geographical areas. Among the numerous vegetation indices available, the NDVI remains one of the most widely used indicators of vegetation greenness and photosynthetic activity. During crop development, NDVI typically follows a characteristic seasonal trajectory corresponding to germination, vegetative growth, peak biomass and senescence. Changes in these trajectories provide valuable insight into crop condition and environmental stress, allowing vegetation responses to climatic variability to be quantified objectively.

3.4.2 However, NDVI alone does not explain why vegetation conditions change. Vegetation responses represent the cumulative outcome of climatic conditions, hazard occurrence and crop suitability. NDVI should therefore be interpreted alongside climatic observations and environmental indicators rather than in isolation. As a result, this study investigates whether the integration of satellite-derived NDVI with climate variables, hazard indices and crop suitability models can provide a more comprehensive understanding of agricultural production dynamics than any single data source alone.

3.5 Study objectives

3.5.1 The aim of this study is to develop and demonstrate a reproducible geospatial framework for assessing climate-related agricultural production risk for maize and wheat in the Free State Province of South Africa. The study is intended as an exploratory and decision-support framework rather than a definitive field-level crop-yield model. Its contribution lies in showing how heterogeneous climate, EO, hazard and agricultural datasets can be reconciled into a transparent analytical structure that supports both scientific interpretation and financial risk applications. The specific objectives are to:

- characterise historical climate variability and ENSO conditions across the Free State, with particular attention to the growing periods of maize and wheat;
- quantify agricultural hazards relevant to crop production, including drought, heatwaves, fire-weather conditions and extreme rainfall;
- delineate the combined maize and wheat production area using harvested-area datasets and use this spatial domain to harmonise climate, hazard and vegetation information;

- analyse seasonal vegetation dynamics using NDVI metrics, including mean greenness, peak greenness, anomalies and time-integrated NDVI;
- estimate crop-specific climatic suitability and introduce an approach to hazard-adjusted suitability using simplified suitability functions;
- construct a crop-year modelling dataset that integrates observed production, planted area, crop productivity, seasonal climate, hazards, ENSO, NDVI and suitability indicators;
- investigate relationships between crop productivity and the selected variables;
- evaluate model performance using in-sample diagnostics and out-of-sample validation; and
- explore how the framework can inform agricultural insurance, lending, portfolio monitoring, climate-related stress testing and broader climate risk management.

3.6 Study area

3.6.1 The study focuses on the Free State Province in South Africa (Figure 1), located within the country's central interior between longitudes of 24°E and 30°E, and latitudes of 26°S and 31°S. The province covers approximately 129,800 km² and is characterised predominantly by open grassland and commercial agriculture.

3.6.2 Rainfall occurs primarily during the summer months (October to April), with annual totals generally ranging between 350 mm in the west and more than

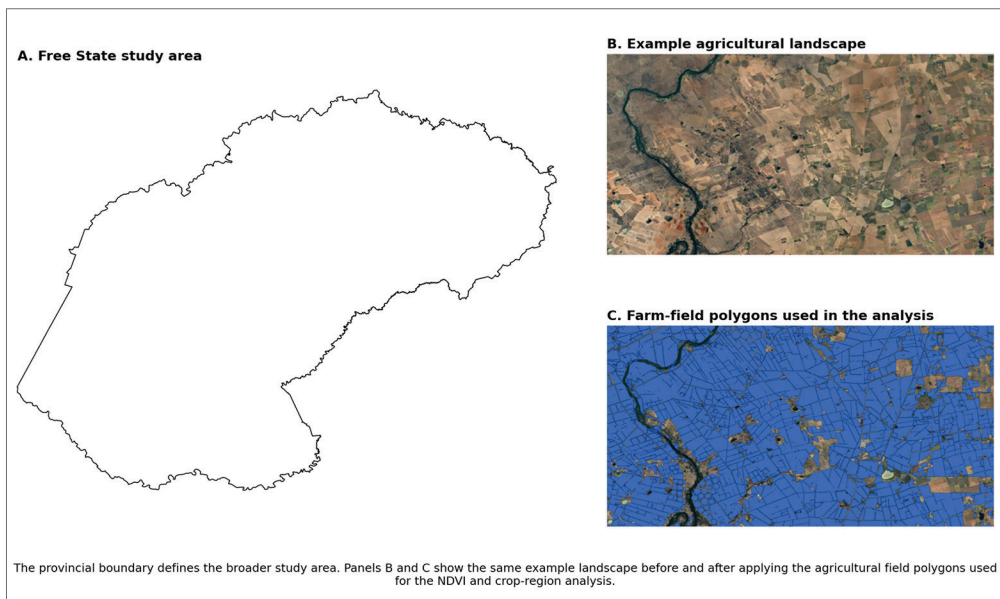


FIGURE 1. Free State study area and agricultural field delineation: (A) shows the provincial study area, (B) and (C) show an example of agricultural landscape before and after applying the farm-field polygons used to spatially constrain the analysis

700 mm in the eastern highlands. Mean annual temperatures typically range between 15°C and 19°C, although substantial seasonal and spatial variability exist due to elevation and continental influences.

3.6.3 Agriculture within the province is dominated by rain-fed and irrigated crop production, particularly maize and wheat, making crop productivity highly dependent upon seasonal rainfall distribution and temperature conditions. Consequently, interannual climate variability associated with ENSO events frequently produces fluctuations in agricultural output.

4. DATA SOURCES

4.1 An integrated geospatial database was developed by combining satellite observation, climate reanalysis datasets, climate variability indices, hazard metrics, crop production statistics and spatial crop distribution information. In general, there are in excess of 642,000,000 data points with various spatial and temporal resolutions utilised in this assessment. Therefore, the datasets in Table 1 were harmonised onto a common spatial grid, allowing environmental conditions experienced within agricultural production areas to be evaluated consistently throughout the analysis.

TABLE 1. Summary of datasets used in the analysis

Dataset	Spatial resolution	Temporal resolution	Period	Usage
ERA5 reanalysis (Copernicus Climate Change Service, 2017)	~31 km	Daily (aggregated from hourly)	1990–Present	Temperature, precipitation and derived climate variables
Oceanic Niño Index (ONI)	Global index	Monthly	1990–Present	Characterisation of ENSO phases and large-scale climate variability
Copernicus Global Land Service NDVI	300 m	10-day composite	2014–Present	Vegetation condition and seasonal productivity metrics
Farm portion	~1 km	Static	2020	Harvested area, production and yield for maize and wheat
South African National Land Cover (SANLC 2022)	20 m	Static	2022	Land-cover validation and agricultural masking
Crop yields	Vector	Annual	1987–Present	Provincial and national level seasonal crop yields
Provincial boundaries	Vector	Static	Current	Study area definition and spatial clipping
Field boundaries	Vector	Static	Current	Study area definition and spatial clipping

4.2 Climate variables were aggregated according to their physical characteristics. Accumulation variables, such as precipitation, were summed over each growing season, whereas variables including temperature, humidity, wind speed and air pressure were averaged over the same period. Seasonal climate metrics were initially calculated for every

climate grid cell before being spatially averaged across the combined maize and wheat production regions.

5. METHODOLOGY

All analyses were implemented in Python and Excel, utilising open-source, statistical and scientific computing libraries. The methodology combined climate, hazard, vegetation, crop distribution, crop productivity and ENSO data to assess environmental influences on maize and wheat productivity in the Free State. The methodology shown in Figure 2 was designed around five sequential components:

- **Data preparation:** Climate, ENSO, vegetation, crop distribution, crop productivity and supporting spatial datasets were collected, quality checked and prepared for analysis.
- **Hazard and suitability assessment:** Climate data were used to calculate drought, heatwave, fire weather and extreme rainfall indicators. Crop-specific climatic suitability was estimated from rainfall and temperature and subsequently adjusted for seasonal hazard conditions.
- **Spatial and seasonal processing:** Crop distribution and ancillary spatial data were used to define the maize and wheat production areas. Environmental variables were then summarised over the relevant growing season for each crop.
- **Vegetation assessment:** NDVI data were assigned to the identified crop areas and

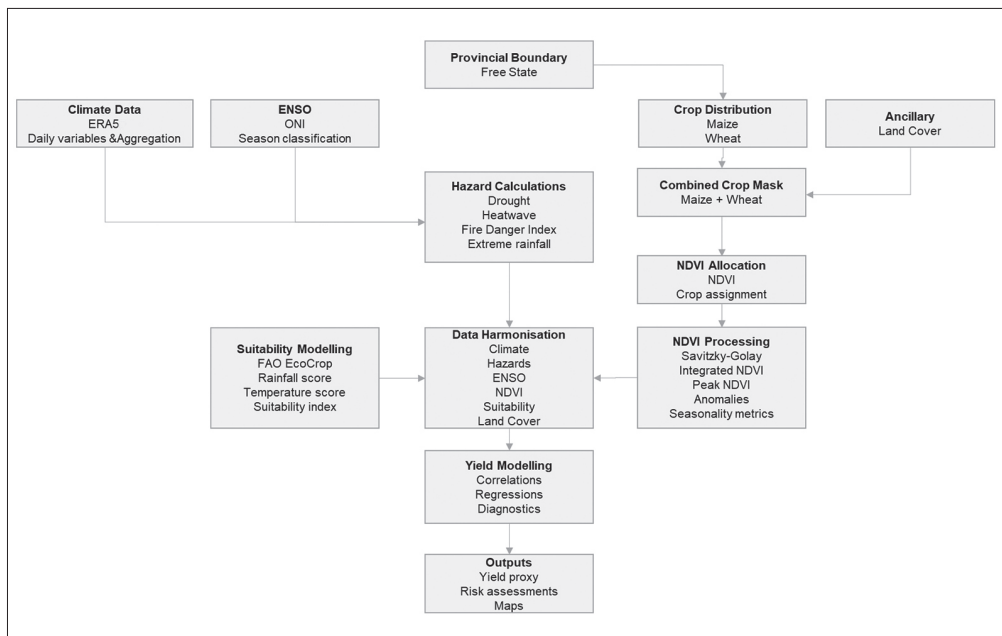


FIGURE 2. Modelling framework of the agricultural assessment, showing the processing and integration of climate, ENSO, hazard, crop distribution, land-cover, suitability and NDVI data prior to crop productivity modelling

processed to derive seasonal vegetation metrics, including mean NDVI, peak NDVI and integrated NDVI.

- **Statistical modelling:** Climate, hazard, ENSO and agricultural variables were combined with observed crop productivity. Correlation analysis and grouped PCA were used to examine and reduce the predictor set. Ordinary Least Squares (OLS) regression was then applied through a hierarchical modelling structure to assess the change in model performance as each information domain was introduced. The statistical hierarchy progressively incorporated four information domains (refer to Section 7.4.7 for more detail). This structure allowed the contribution of additional environmental information to be assessed while retaining the preceding information domains. Model performance and potential overfitting were assessed using leave-one-year-out (LOYO) cross-validation.

5.1 Study area delineation

5.1.1 Administrative boundaries obtained from South African provincial boundary datasets were used to define the spatial extent of the analysis. All datasets were transformed into a common geographic coordinate reference system to ensure consistency throughout the workflow.

5.1.2 Climate variables, hazard indices, satellite imagery and agricultural datasets were spatially restricted to the provincial extent prior to further processing. Furthermore, spatial analyses were restricted to the combined maize and wheat production regions identified using the harvested-area dataset together with agricultural field boundaries.

5.1.3 Separate harvested-area raster datasets were processed for maize and wheat. Cells containing harvested area greater than a predefined threshold were retained. The two crop layers were subsequently merged to produce a combined agricultural mask representing all major maize and wheat production regions within the Free State.

5.1.4 This combined crop region formed the spatial basis for all crop analyses. Additional raster datasets describing production, yield and land cover were intersected with the crop polygons to provide supporting agricultural information for later analyses.

5.1.5 Restricting the analysis to the combined crop region reduces bias introduced by natural vegetation, urban areas and other non-agricultural land cover while ensuring that environmental metrics represent conditions experienced within agricultural-producing regions.

5.2 Crop season

5.2.1 Crop seasons were defined using the Food and Agriculture Organization (FAO) crop calendar for South Africa shown in Figure 3. To ensure temporal consistency, all environmental variables, including climate, climate hazards, NDVI, crop suitability and ENSO indices, were initially aggregated to monthly values before being summarised over each crop's growing season. These seasonal summaries formed the basis of the subsequent correlation and regression analyses.

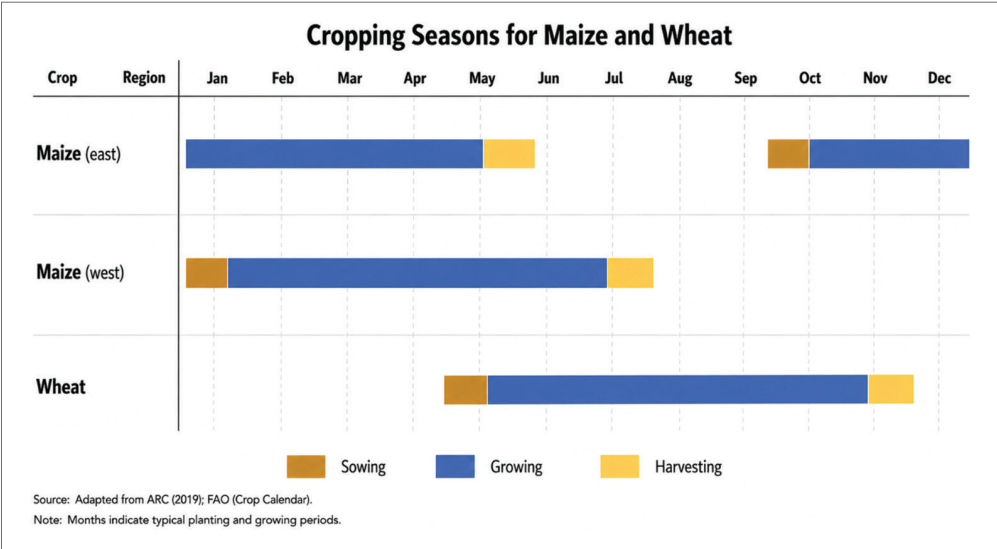


FIGURE 3. Crop-specific growing seasons used to define seasonal climate and vegetation metrics for maize and wheat

5.2.2 Maize is a summer crop grown between September and May, with the growing season spanning two calendar years. Climatic variables for each maize season were therefore aggregated across both years and assigned to the harvest year (e.g., September 2009–May 2010 = 2010 season). Winter wheat is grown between May and October within a single calendar year and was analysed using the corresponding calendar year (Table 2).

TABLE 2. Crop-specific growing periods and harvest-year conventions used in the seasonal analysis

Crop	Growing period	Harvest year
Maize	September – May	Year in which harvest occurs
Wheat	May – November	Calendar year

5.3 Climate data

Climate data were analysed using the procedures described in Appendix A.1, which details the climate variables, processing and aggregation of the individual climate variables. This includes rainfall-specific aggregation considerations.

5.4 Hazard assessment

Agricultural productivity is influenced by both average climatic conditions and the occurrence of extreme weather or hazard events. Hazard indicators were therefore derived from daily climate data using standardised definitions, metrics and thresholds. Table 3

provides a summarised view of the hazard variables used in the subsequent analysis, together with their thresholds, seasonal aggregation and units. Detailed definitions, calculations and methodological assumptions for each hazard indicator are provided in Appendix A.

TABLE 3. Hazard definitions, thresholds and seasonal aggregation metrics used in the analysis

Hazard	Metric	Threshold	Seasonal aggregation	Units
Drought	$SPI_t^{(k)}$	≤ -1.0	Mean standardised precipitation index (SPI), minimum SPI, drought days	Dimensionless, days
Heatwave	Heatwave days	90th percentile for ≥ 3 consecutive days	Mean event days	Days
Extreme rainfall	Daily rainfall	>95 th percentile	Event days, rainfall from events	Days, mm
Fire weather	Fire weather proxy	90–95th percentile	Mean index, high fire danger days	Index, days

5.5 Crop suitability assessment

5.5.1 Crop suitability was evaluated using a simplified FAO EcoCrop-based (FAO, 1998) approach. Separate suitability functions were developed for maize and wheat using crop-specific seasonal rainfall and mean temperature thresholds (Table 4).

TABLE 4. Crop suitability thresholds used for maize and wheat

Crop	Variable	Minimum	Optimum lower	Optimum upper	Maximum
Maize	Seasonal rainfall (mm)	400	600	900	1200
Maize	Mean temperature (°C)	10	18	27	35
Wheat	Seasonal rainfall (mm)	250	300	450	600
Wheat	Mean temperature (°C)	2	10	18	28

5.5.2 Suitability for each climatic variable was expressed on a scale from 0 to 1, with values of 1 representing the defined optimum range and lower values representing progressively less favourable conditions. Overall climatic suitability was determined using the limiting-factor principle:

$$S_{\text{climate}} = f(S_{\text{rainfall}}, S_{\text{temperature}})$$

where:

- S_{climate} is the climatic suitability score;
- S_{rainfall} is the seasonal rainfall suitability score; and
- $S_{\text{temperature}}$ is the mean temperature suitability score.

5.5.3 This metric represents climatic favourability based on seasonal rainfall and temperature but does not explicitly account for adverse extreme weather or hazard

events occurring during the growing season. A second, hazard-adjusted suitability score (S_{HA}) was therefore calculated by applying hazard-specific penalties for drought, heatwave, fire weather and extreme rainfall:

$$S_{HA} = S_{\text{climate}} \times P_{\text{drought}} \times P_{\text{heatwave}} \times P_{\text{fire}} \times P_{\text{extreme rainfall}}$$

where P_i is the hazard-specific penalty function associated with hazard i . Each penalty ranges between 0 and 1:

- $P_i=1$ indicates no reduction in suitability;
- S_{climate} is the climatic suitability score; and
- P_i represents the multiplicative penalty associated with each hazard.

5.5.4 Penalty functions were assigned by considering crop-hazard severity, sensitivity, and the lagged effect of each hazard.

5.5.5 Both climatic suitability and hazard-adjusted suitability were evaluated in the subsequent statistical analysis alongside climate, hazard, ENSO and vegetation variables.

5.6 Statistical analysis

5.6.1 Relationships between seasonal crop productivity and environmental conditions were investigated using a hierarchical modelling framework combining PCA and OLS regression. Separate analyses were undertaken for maize and wheat to account for their contrasting growing seasons and climatic requirements.

5.6.2 Candidate environmental variables describing seasonal climate, climatic hazards, vegetation dynamics, climatic suitability and ENSO were first examined using Pearson and Spearman correlation analyses to identify relationships among predictors and with crop productivity.

5.6.3 To reduce dimensionality and minimise multicollinearity, predictor variables were grouped into four progressively more comprehensive environmental hierarchies:

- climate,
- climate and climatic hazards,
- climate, climatic hazards and ENSO, and
- climate, climatic hazards, ENSO and agriculture.

5.6.4 Prior to PCA, all predictor variables within each hierarchy were standardised using z-score normalisation to ensure that variables measured on different numerical scales contributed equally to the derivation of principal components. Separate PCAs were then performed for each hierarchy, and the retained principal components were used as orthogonal predictors in the subsequent regression analyses.

6. EXPLORATORY ANALYSIS

6.1 Climate variability and ENSO

6.1.1 The ONI provides a measure of interannual climate variability associated with ENSO and its influence on Southern African climate. Throughout the study period (1990–2025), the ONI oscillated between El Niño and La Niña conditions, with several moderate to very strong events observed (Figure 4).

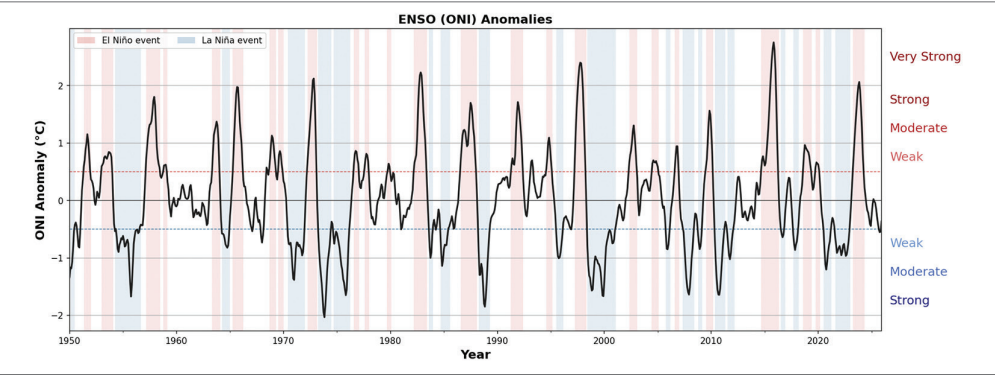


FIGURE 4. Historical variability in the Oceanic Niño Index and classification of El Niño and La Niña events (1950–2025)

6.1.2 ENSO cycles are classified by their ONI values using Table 10 in Appendix A.2. Notable El Niño episodes occurred during 1982–1983, 1997–1998, and 2015–2016, whilst extended La Niña conditions occurred during 1998–2001, 2010–2012 and 2020–2022.

6.1.3 Figure 5 compares the observed 2026 ONI trajectory with the development of the major 1982–1983, 1997–1998 and 2015–2016 El Niño events. The gradient of this trajectory is steeper than that observed over the corresponding development period of the historical events shown, indicating more rapid early-season strengthening of the Pacific warming signal. This suggests that the agricultural sector may face more rapid and potentially more severe climate stress than experienced during previous major El Niño episodes.

6.1.4 The seasonal persistence of ENSO is important for South African agriculture because its influence on rainfall can extend across much of a growing season rather than being restricted to individual months. ENSO can therefore alter the probability and spatial distribution of rainfall deficits, drought conditions and other climate hazards that ultimately influence crop productivity.

6.2 Long-term climate trends

Climate data were analysed using the procedures described in Appendix A.1 (the processing, aggregation and treatment of the individual climate variables, including rainfall-specific considerations).

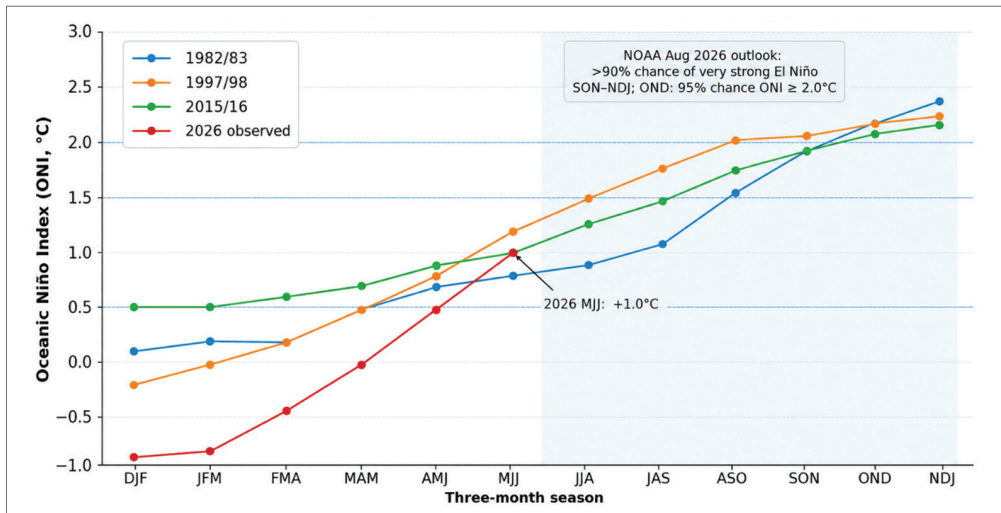


FIGURE 5. Development of the 2026 El Niño relative to major historical El Niño events based on the Oceanic Niño Index

6.2.1 Temperature

6.2.1.1 The annual temperature time series indicates a warming trend across the Free State throughout the study period. Both minimum and maximum temperatures exhibit positive trends, although increases in maximum temperature are generally more pronounced during the summer growing season (Figure 6).

6.2.1.2 Five-year moving averages demonstrate that temperatures have remained consistently above the long-term climatological mean since approximately the early 2000s, suggesting that warming is not the result of short-term climatic variability but reflects a long-term change.

6.2.1.3 Spatial analyses reveal that warming is relatively homogeneous across the province, although local variations associated with elevation and topography remain evident. The contour maps indicate slightly cooler conditions across the eastern regions, while western regions generally experience higher seasonal temperatures.

6.2.2 Rainfall

6.2.2.1 Annual rainfall varied considerably between 1990 and 2025. Wet and dry years alternated with no sustained increase or decrease across the full period (Figure 7A). The fitted linear trend indicates a small decline in annual rainfall of approximately 1.9 mm per year, although this change is small relative to the year-to-year variability. Several years exceeded 900 mm, while the driest years received less than 500 mm. The five-year moving average also shows periods of persistently wetter and drier conditions, including a decline during the early to mid-2010s followed by wetter conditions from approximately 2019 onwards. These periods correspond closely with ENSO cycles (Figure 4).

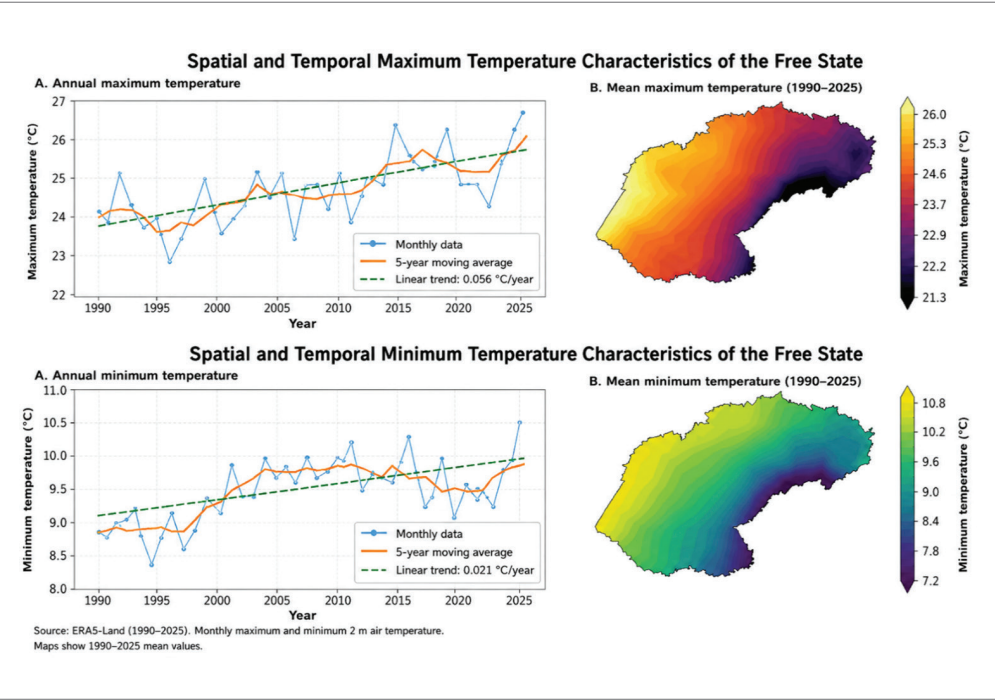


FIGURE 6. Spatial and temporal temperature characteristics of the Free State: (A) average maximum and minimum temperatures, including the five-year moving average and linear trend; and (B) mean average temperature across the province over the same period (1990–2025)

6.2.2.2 Rainfall differs spatially across the Free State (Figure 7B). Mean annual rainfall increases from approximately 450–550 mm in the west to more than 900 mm in parts of the east and north-east. This gradient produces different baseline rainfall conditions across the province which is important when interpreting provincial-scale climate and agricultural indicators. In summary, a rainfall deficit of similar magnitude may represent different conditions and impacts depending on where it occurs.

6.3 Agricultural hazards

6.3.1 Long-term climate trends describe the general conditions under which crops are grown; however they can mask extreme weather or hazard events within a crop growing season. Four agricultural hazards were therefore assessed across the Free State utilising the indices and thresholds in Table 3.

6.3.2 Hazard metrics were calculated over crop-specific growing seasons (Table 2) to represent the conditions experienced during crop development. This provides a measure of seasonal hazard exposure that can be compared with crop productivity in subsequent analyses.

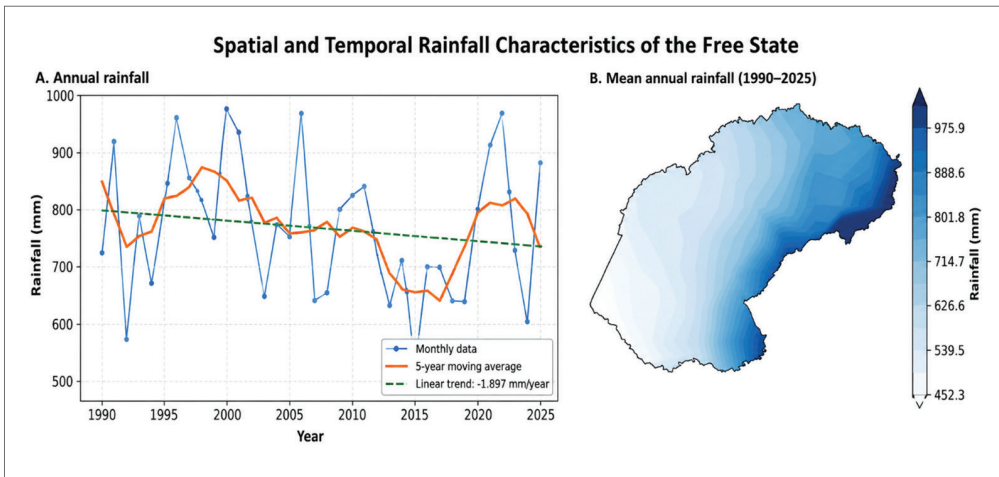


FIGURE 7. Spatial and temporal rainfall characteristics of the Free State: (A) annual rainfall, including the five-year moving average and linear trend; and (B) mean annual rainfall across the province over the same period (1990–2025)

6.3.3 Drought

6.3.3.1 Drought conditions were assessed using the Standardised Precipitation Index (SPI) with a detailed definition, and formulae provided in Appendix A.3. Multiple accumulation periods were considered to distinguish short-term rainfall deficits from more persistent drought conditions.

6.3.3.2 Figure 8 illustrates varying drought conditions for different accumulation scales (SPI-1, SPI-3, SPI-6 and SPI-12) between 1990 and 2025. As expected, shorter accumulation periods exhibit greater temporal variability, whereas longer accumulation periods emphasise sustained drought conditions. SPI-1 responds rapidly to individual rainfall events and therefore displays considerable short-term variability. SPI-3 provides a smoother representation of seasonal moisture conditions and is particularly relevant to agricultural drought affecting crop growth. SPI-6 further suppresses short-term fluctuations and highlights persistent seasonal moisture deficits, while SPI-12 reflects long-term hydrological drought cycles associated with prolonged wet and dry periods.

6.3.3.3 Several extended drought episodes are evident throughout the study period, with the most severe occurring during the 2015–2016 El Niño event. This event produced prolonged negative SPI values across multiple accumulation periods, indicating both seasonal agricultural drought and longer-term moisture deficits.

6.3.3.4 The classification of SPI values in Figure 9 shows that dry conditions occurred throughout the study period. These conditions are not only confined to major drought years. Moderate and severe drought conditions are relatively frequent at shorter accumulation periods, while extreme drought becomes more apparent when deficits persist across several months.

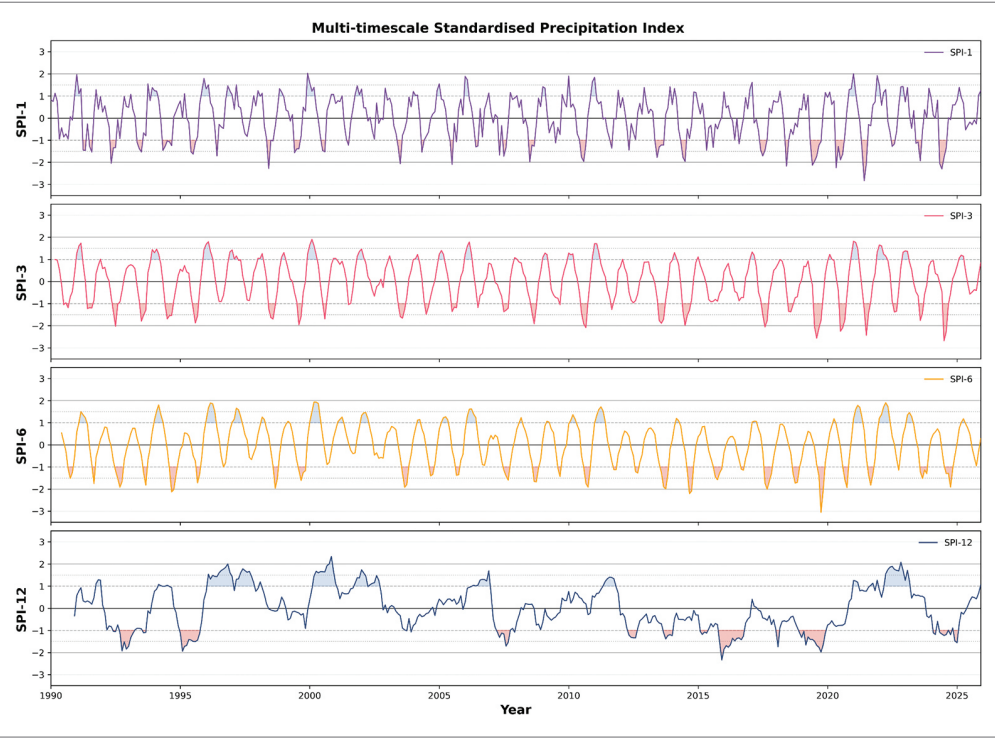


FIGURE 8. SPI across multiple accumulation periods in the Free State (1990–2025)

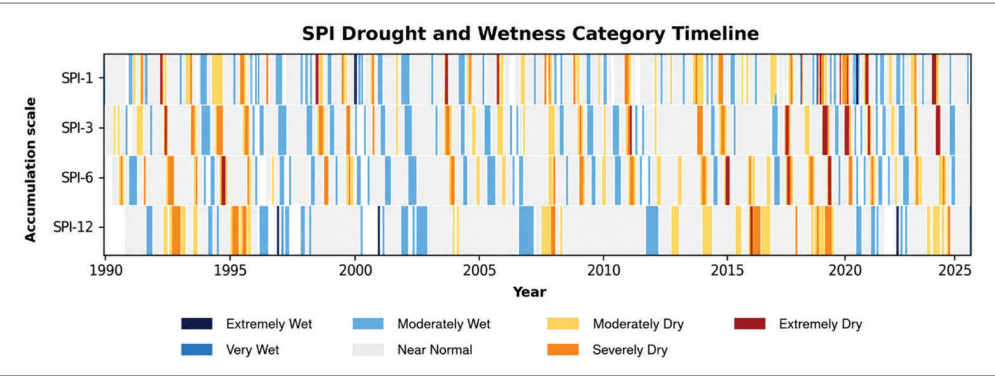


FIGURE 9. Temporal classification of drought and wetness conditions across SPI accumulation periods (1990–2025)

6.3.3.5 Periods where drought conditions across multiple accumulation scales stand out. The 2015–2016 period is notable, with negative SPI conditions extending from the shorter accumulation periods through to SPI-12. This indicates that the rainfall deficit was not limited to short-term variability but formed part of a prolonged dry period in the region.

6.3.3.6 Figure 10 summarises the duration and severity of drought events derived from the SPI analysis. The longer events are interesting from an agricultural point of view because they represent sustained rainfall deficits that may extend across different stages of crop growth and development. The longest events occurred between 2015–2016 and 2019–2020, with durations of approximately 12 and 13 months, respectively. These prolonged events demonstrate that drought exposure in the Free State is not limited to dry months and can persist across successive seasons.

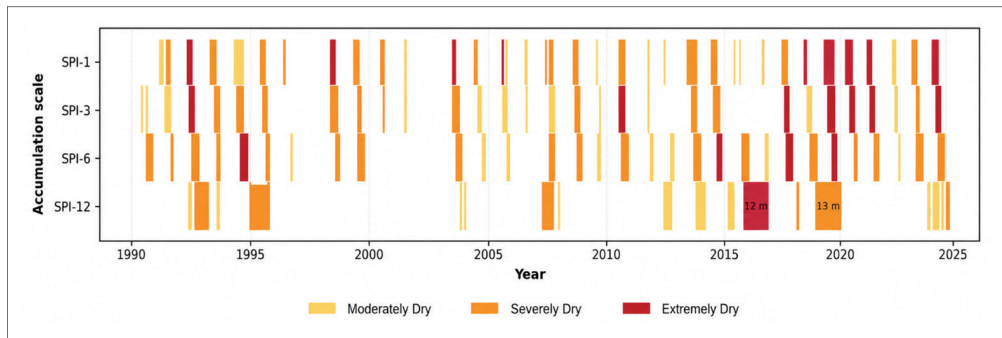


FIGURE 10. Duration and timing of drought events across SPI accumulation periods (1990–2025)

6.3.4 Heatwaves

6.3.4.1 Heatwave occurrences were assessed using metrics described in Table 3 and Appendix A.4. Heatwave occurrence exhibited substantial interannual variability throughout the study period illustrated in Figure 11A. Although heatwave events were recorded across most years, both their frequency and persistence increased during the last decade. The five-year moving average indicates an overall upward trend in heatwave occurrence from 2010. The highest frequencies occurred in 2015 and 2024–2025, with more than 15 events recorded in some years.

6.3.4.2 Figure 11B demonstrates that heatwaves occur predominantly during the warmer months, with events concentrated between October and March. This seasonality overlaps with the maize growing season and is therefore particularly relevant to summer crop production. Severe and extreme events are also more prominent during the latter part of the record, particularly from the mid-2010s onwards.

6.3.4.3 Spatially, the highest heatwave frequencies occurred across the warmer central and northern regions of the province illustrated in Figure 11C. This pattern broadly corresponds with the spatial temperature differences identified in the climatic analysis.

6.3.4.4 The concentration of these events during the summer growing season provides a direct link to the effect which increasing temperature extremes may have on agricultural production. Heatwave exposure was therefore included in the hazard-adjusted suitability assessment and subsequent analysis of crop productivity.

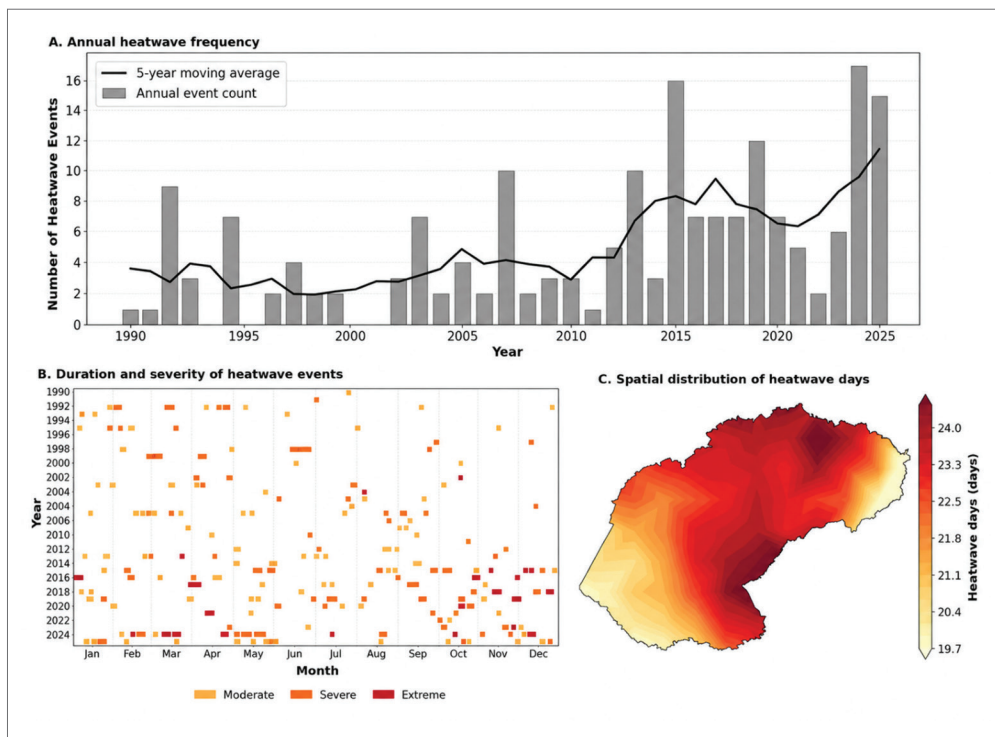


FIGURE 11. Temporal, seasonal and spatial characteristics of heatwaves in the Free State in the period 1990–2025: (A) annual heatwave frequency, including the five-year moving average; (B) timing and severity of heatwave events by month and year; and (C) mean annual heatwave days across the province

6.3.5 Flood hazard

6.3.5.1 Flood hazard was represented using the extreme rainfall metrics described in Table 3 and Appendix A.6. While seasonal rainfall totals describe overall water availability, extreme rainfall metrics identify periods of intense precipitation that may contribute to flooding, waterlogging, soil erosion and crop damage.

6.3.5.2 Figure 12A highlights year-to-year variability in flood hazard, with no clear long-term increasing or decreasing trend. Instead, flood activity is characterised by isolated years with elevated numbers of extreme rainfall events, particularly during the late 1990s and the period from 2020 to 2022. These years broadly coincide with wetter climatic conditions and La Niña phases, although extreme rainfall events also occur during neutral and El Niño conditions. This highlights that flood hazard remains an important hazard irrespective of the prevailing ENSO phase, although its likelihood increases during wetter years.

6.3.5.3 The timing of extreme rainfall events shows a strong seasonal pattern (Figure 12B). Events are concentrated between October and March, corresponding with

the summer rainfall season and much of the maize growing period. Severe and extreme events occur throughout the study period, including during years where the total number of events is comparatively low. The spatial distribution of maximum five-day rainfall shows an east–west gradient (Figure 12C). The highest cumulative rainfall occurs across the eastern and north-eastern Free State, while substantially lower values occur towards the western parts of the province.

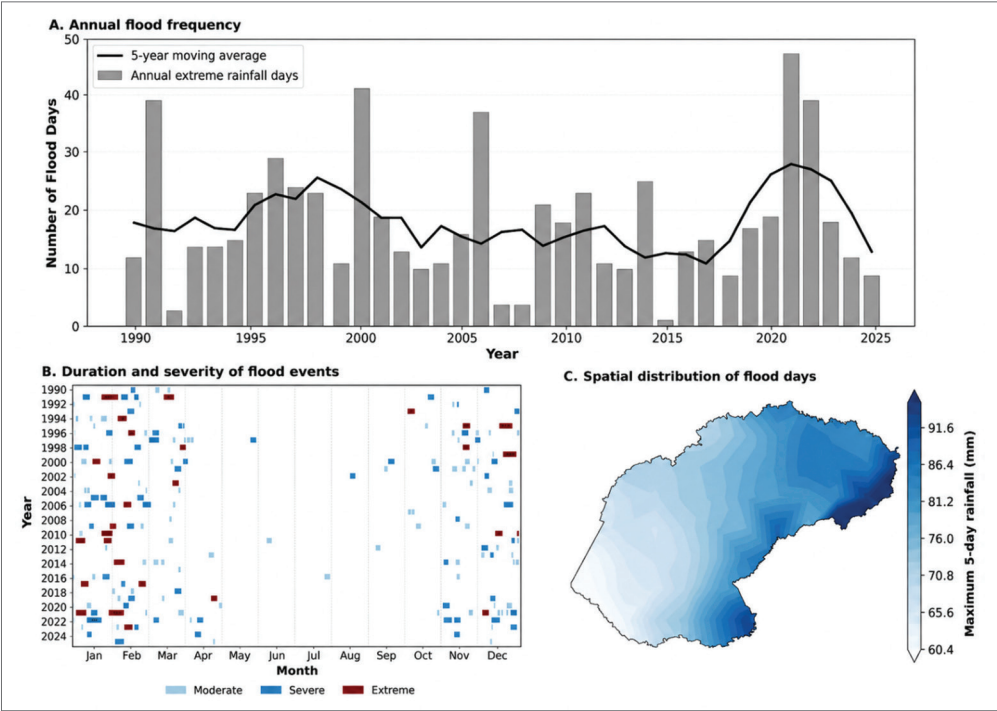


FIGURE 12. Temporal, seasonal and spatial characteristics of floods in the Free State in the period 1990–2025: (A) annual flood frequency, including the five-year moving average; (B) timing and severity of flood events by month and year; and (C) maximum cumulative five-day rainfall across the province

6.3.5.4 The results show that extreme rainfall hazard in the Free State is characterised by temporal variability, seasonality and spatial concentration. For agricultural production, extreme rainfall was considered separately from seasonal rainfall because similar seasonal rainfall totals may result from frequent moderate rainfall or a smaller number of intense events.

6.3.6 Fire weather

6.3.6.1 Fire-weather conditions were characterised using the composite fire weather proxy from Table 3 and Appendix A.5, which combines maximum temperature,

wind speed, relative humidity, antecedent rainfall and the duration since meaningful rainfall. Higher proxy values indicate conditions that are more favourable for vegetation drying and fire spread. High fire danger days occur predominantly during dry years characterised by reduced rainfall and elevated temperatures.

6.3.6.2 Figure 13A shows the spatial distribution of mean fire-weather conditions across the Free State. Higher values occur predominantly in the western and south-western parts of the province, with progressively lower values towards the east. This pattern broadly follows the provincial climatic gradient, with the western Free State generally experiencing warmer and drier conditions.

6.3.6.3 Annual seasonal cycles of fire-weather conditions are given by Figure 13B. In general, the proxy increases from May, with the highest mean values occurring between August and October. Conditions subsequently decline towards the summer rainfall season, indicating that late winter and early spring represent the principal period of elevated fire-weather conditions.

6.3.6.4 The interannual variability in the mean fire-weather proxy during the peak season of August–October is shown in Figure 13C. In general, year-to-year variability is evident, while the five-year moving average increases from the early 1990s to around 2010. Peak-season conditions remain relatively elevated thereafter, although interannual variability persists, with individual years such as 2009 and 2019 exhibiting particularly high values.

6.4 Spatial distribution of agricultural production and yield data

6.4.1 Spatial harvested-area data were used to identify the principal maize- and wheat-growing regions within the Free State. Figure 14A shows that maize cultivation

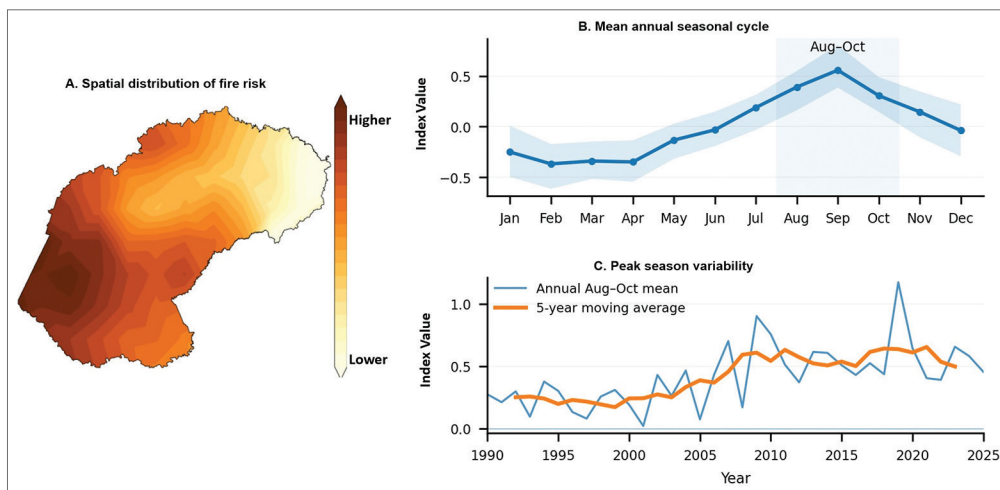


FIGURE 13. Spatial and temporal variability in fire-weather conditions across the Free State: (A) Long-term spatial distribution of relative fire-weather conditions; (B) Mean monthly seasonal cycle; (C) Interannual variability in the in the fire-weather conditions August–October

is concentrated across the central, northern and eastern parts of the province, while Figure 14B shows a broadly similar but less extensive distribution for wheat. Both crops have comparatively limited harvested area in the south-western Free State.

6.4.2 The harvested-area data were used solely to define the spatial extent of crop production and were not used as estimates of annual harvested area or yield. The maize and wheat harvested-area layers were combined to produce a combined crop region representing the primary crop regions of the province Figure 14C. This combined crop region formed the spatial basis for subsequent analyses, including the extraction of NDVI and climatic variables, ensuring that environmental indicators were calculated only for areas where crop production occurs.

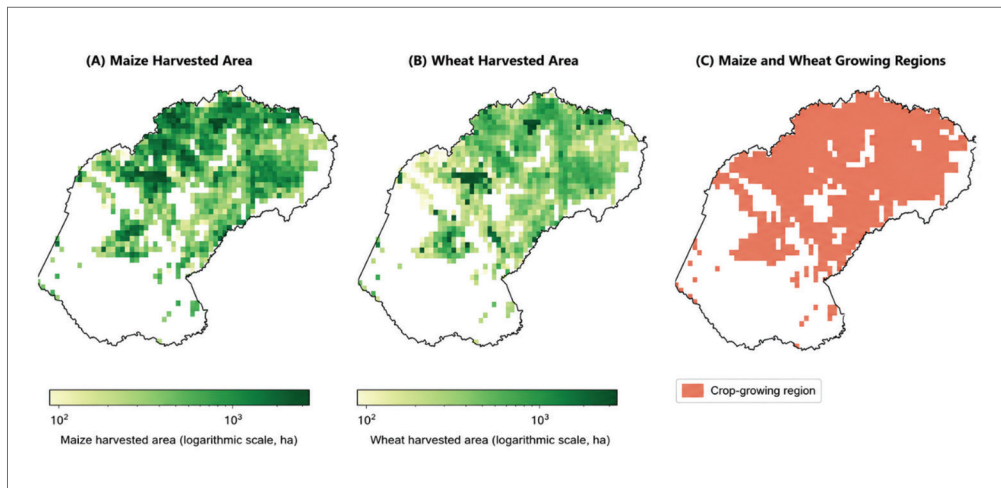


FIGURE 14. Spatial distribution of maize and wheat harvested area and the derived crop-growing region in the Free State: (A) maize, (B) wheat, and (C) the combined crop-growing region

6.4.3 Provincial level crop statistics for maize and wheat, including harvested area (ha), total production (t) and productivity (t ha^{-1}), were obtained from the Department of Agriculture.¹ The available reporting periods differ for maize and wheat due to differences in historical data availability. However, the study period is covered in the reported data. Figure 15 shows these indices as values relative the first available year of data.

6.4.4 In general, productivity has increased annually across South Africa and the Free State for maize and wheat. Maize production has seen a stable footprint, whereas wheat exhibits a downward trend. This downward trend could indicate farmers diversifying their winter crops by exploring more cost-effective cultivars. The decreased maize production and productivity in the Free State during 2015–2016 coincides with

1 Department of Agriculture (n.d.). Crop Estimates. Republic of South Africa. Available at: <https://www.nda.gov.za/index.php/publication/320-crop-estimates?>

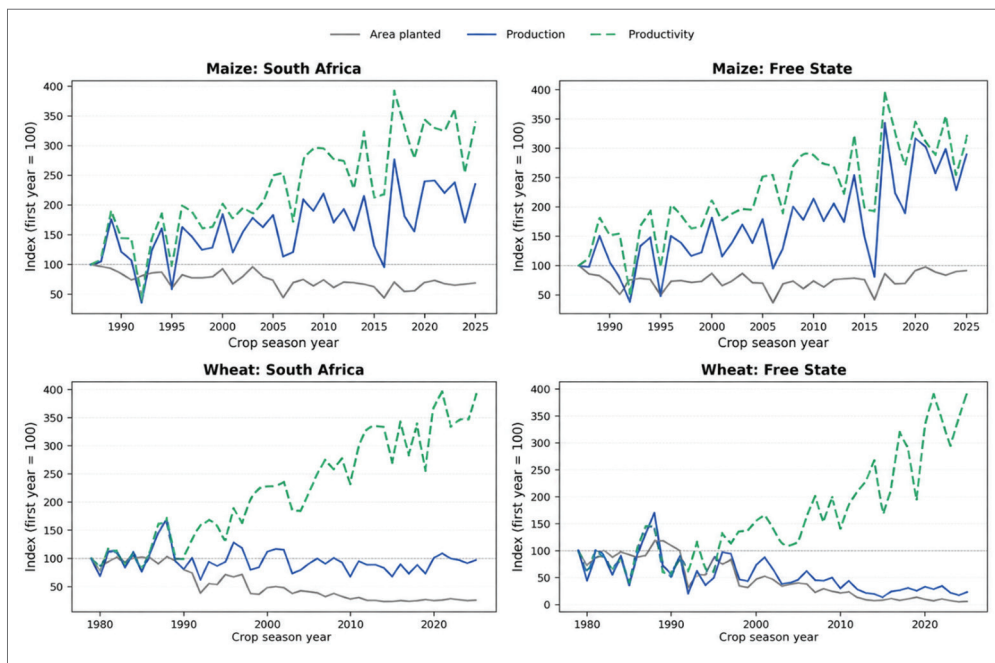


FIGURE 15. Indexed changes in area planted, production and productivity for maize and wheat in South Africa and the Free State

the drought conditions identified by the SPI analysis in Figures 9 and 10, indicating an example of the relationship between climate hazards and agricultural outcomes.

7. RESULTS

7.1 Crop climate suitability

7.1.1 Crop climate suitability provides an estimate of the climatic favourability for maize and wheat production based on crop-specific seasonal rainfall and mean temperature requirements described in Table 4. Furthermore, the crop climate suitability was only evaluated for the crop growing seasons given in Figure 3. The long-term mean climatic suitability across the Free State is shown in Figure 16.

7.1.2 For both crops, climatic suitability generally increases from west to east, reflecting the provincial rainfall gradient and more favourable climatic conditions in the eastern Free State. However, the spatial gradient of wheat indicates that the crop is less spatially constrained than maize.

7.1.3 Higher suitability scores indicate a region having more favourable rainfall and temperature conditions for the crop. Although lower suitability regions indicate unfavourable rainfall and temperature conditions, it does not indicate that crop production is not viable. Instead, lower scores indicate regions that may require greater management actions such as irrigation.

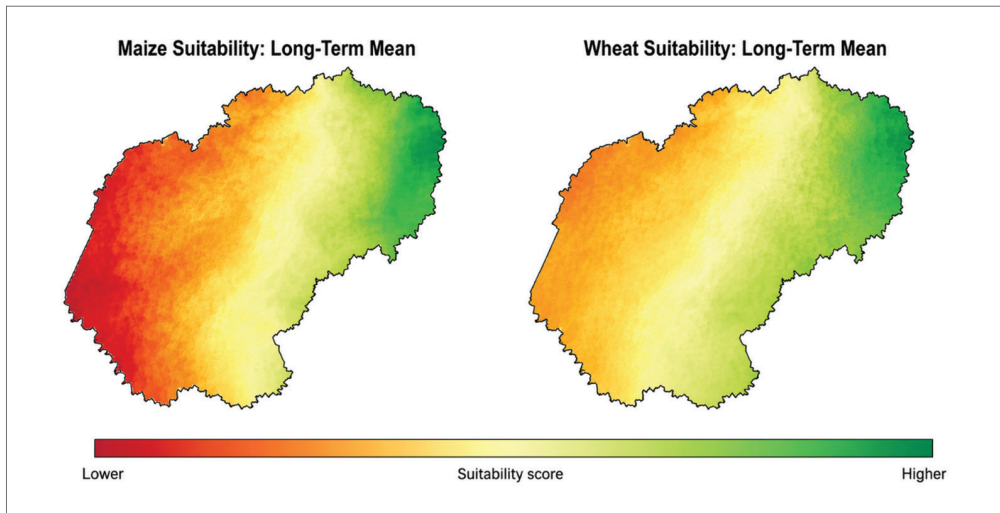


FIGURE 16. Long-term mean climatic suitability for maize and wheat across the Free State

7.2 Crop hazard-adjusted suitability

7.2.1 Climatic suitability describes the favourability of crop-specific seasonal rainfall and temperature conditions but does not explicitly account for climate extremes or hazards occurring within the growing season. To incorporate this additional information, climatic suitability was adjusted using the seasonal hazard metrics described in Section 6.3. The resulting hazard-adjusted suitability retains the climatic suitability score while applying penalty functions based on the frequency and severity of hazards during each crop season.

7.2.2 Figure 17 compares climatic and hazard-adjusted suitability for maize (A) and wheat (B). Hazard adjustment reduced mean suitability by 14% and 18% for maize and wheat respectively. The reduction is non-linear between seasons because these differences reflect the combined effects of drought, heatwaves, extreme rainfall and fire-weather conditions. Therefore, their potential cumulative or lagged effects are included in the suitability.

7.2.3 The hazard-adjusted suitability provides a more realistic representation of seasonal agricultural conditions because it combines long-term climatic favourability with the realised impacts of weather extremes. This metric was used in the subsequent statistical modelling to evaluate whether incorporating seasonal climate hazards improves the explanation of interannual crop productivity relative to climatic suitability alone.

7.3 Vegetation dynamics

7.3.1 Satellite-derived NDVI was used to characterise seasonal vegetation development within the combined crop regions of the study, according to Appendix A.7.

7.3.2 Three seasonal metrics were calculated for each growing season:
— seasonal mean NDVI;

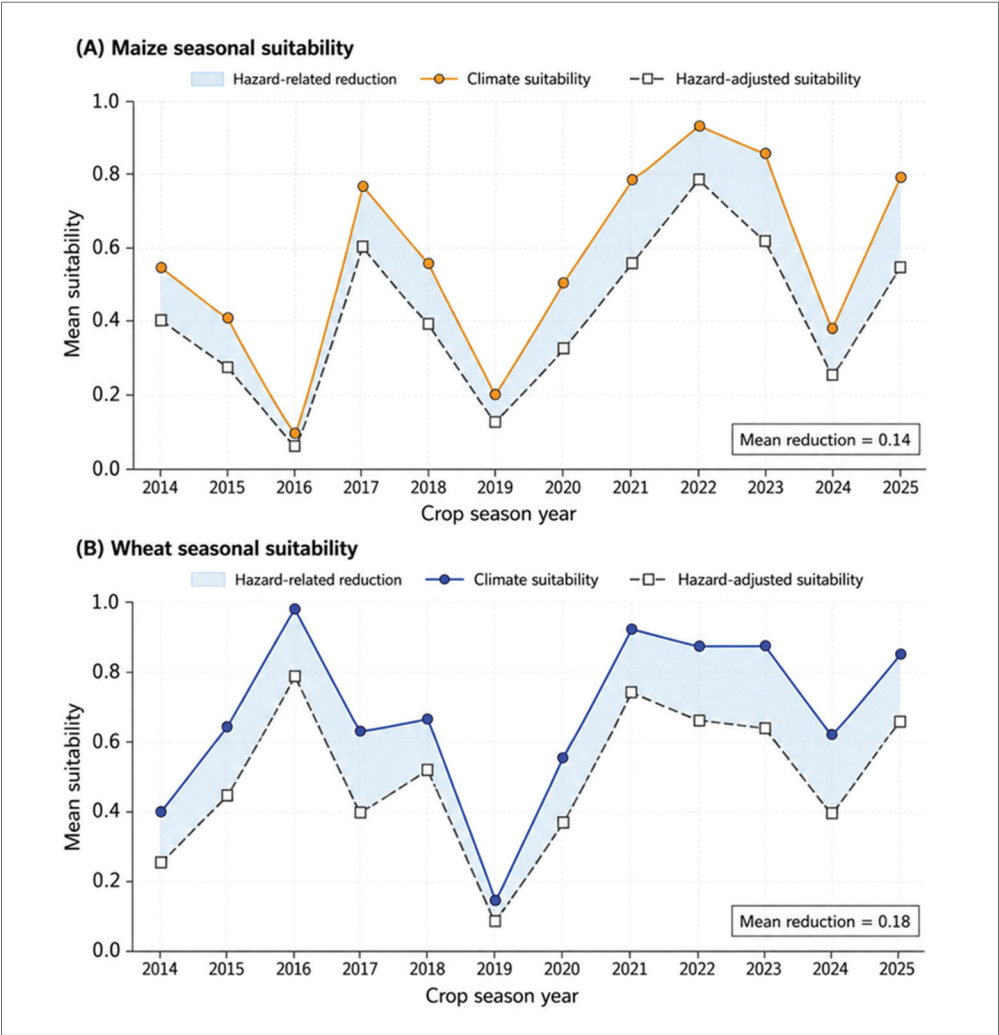


FIGURE 17. Seasonal climate and hazard-adjusted suitability for (A) maize and (B) wheat in the Free State (2014–2025)

- peak NDVI; and
- seasonal integrated NDVI (NDVI area under the curve (AUC)).

7.3.3 Seasonal mean NDVI represents the average vegetation condition throughout the growing season, while peak NDVI reflects the maximum canopy development achieved. NDVI AUC was used as the principal vegetation metric in subsequent analyses because it captures vegetation development across the full crop-growing season rather than conditions at a single point in time.

7.3.4 Seasonal vegetation development

Figure 18 illustrates the monthly NDVI cycle across the assessment period relative to the long-term mean. Although there are clear seasonal cycles observed, individual years deviate from this mean seasonal pattern, particularly in the timing and magnitude of vegetation development. This interannual variability provides a basis for comparing seasonal vegetation response with observed crop productivity, particularly when vegetation development is integrated across the growing season using NDVI AUC.

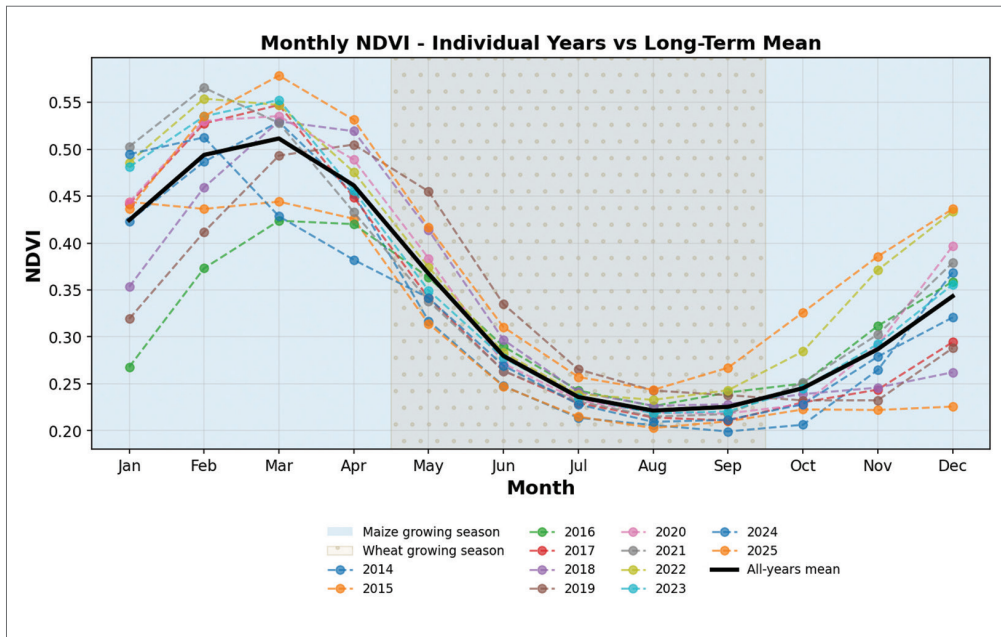


FIGURE 18. Monthly NDVI across Free State crop-growing regions for individual years and the long-term mean (2014–2025)

7.3.5 Seasonal NDVI anomalies

7.3.5.1 Seasonal NDVI AUC was used to compare cumulative vegetation development between growing seasons for each crop.

7.3.5.2 Figure 19 illustrates the year-on-year changes in NDVI AUC for the combined crop cycle (A), highlights the maize summer crop season (B), and the wheat winter crop season (C) in the Free State. Positive anomalies indicate seasons with above-average vegetation development, whereas negative anomalies correspond to reduced seasonal growth.

7.3.5.3 Comparing the anomaly analysis for various seasons shows that climatic conditions do not necessarily affect maize and wheat equally. Several growing seasons exhibit below-average vegetation development for one crop while the other remains close to or above average. Separating the crop seasons reveals that these changes are not always

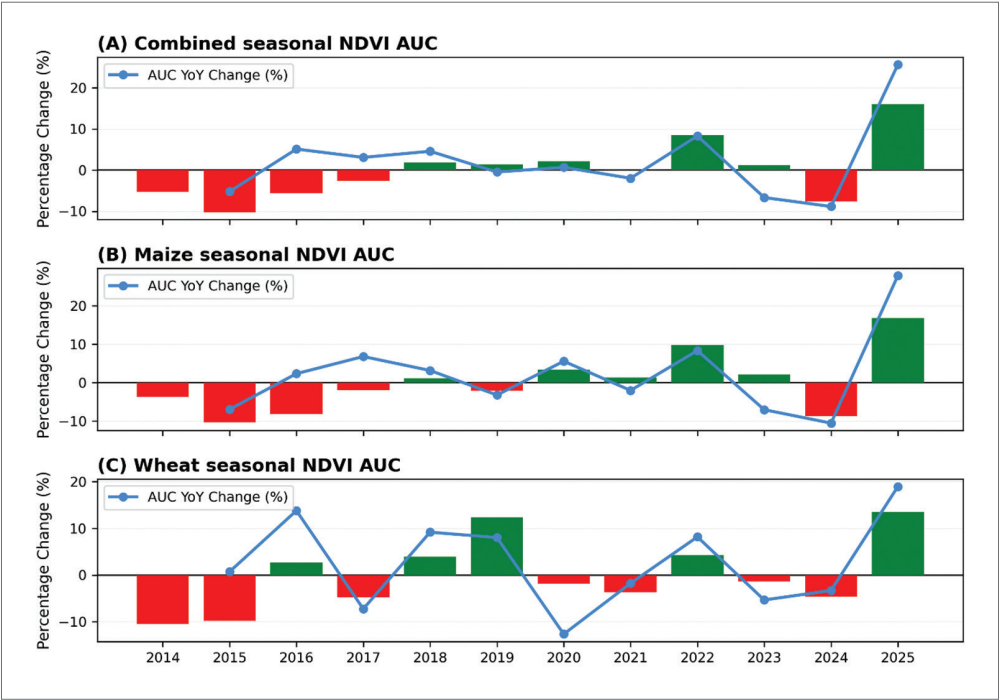


FIGURE 19. Seasonal NDVI AUC variability for (A) combined maize and wheat, (B) maize, and (C) wheat in the Free State (2014–2025)

consistent between maize and wheat. For example, the maize and wheat series differ in both the magnitude and direction of change in several years. These differences reflect the contrasting timing of the summer maize and winter wheat growing seasons and show that an annual or combined vegetation signal can mask crop-specific responses.

7.3.6 Relationship between vegetation and suitability

7.3.6.1 Figure 20 compares normalised seasonal NDVI AUC anomalies with observed provincial crop yield anomalies. For maize (Figure 20A), several changes in NDVI AUC coincide with changes in yield, including the lower values around 2015–2016 and 2019 and higher values in 2017 and 2023. For wheat (Figure 20B), the relationship is less consistent, with NDVI AUC and yield moving in the same direction in some seasons but diverging in others. This suggests that seasonal vegetation development captures information relevant to crop productivity but does not provide a direct proxy for annual yield.

7.3.6.2 Unlike the climate and hazard indicators, NDVI measures the observed vegetation response during the growing season.

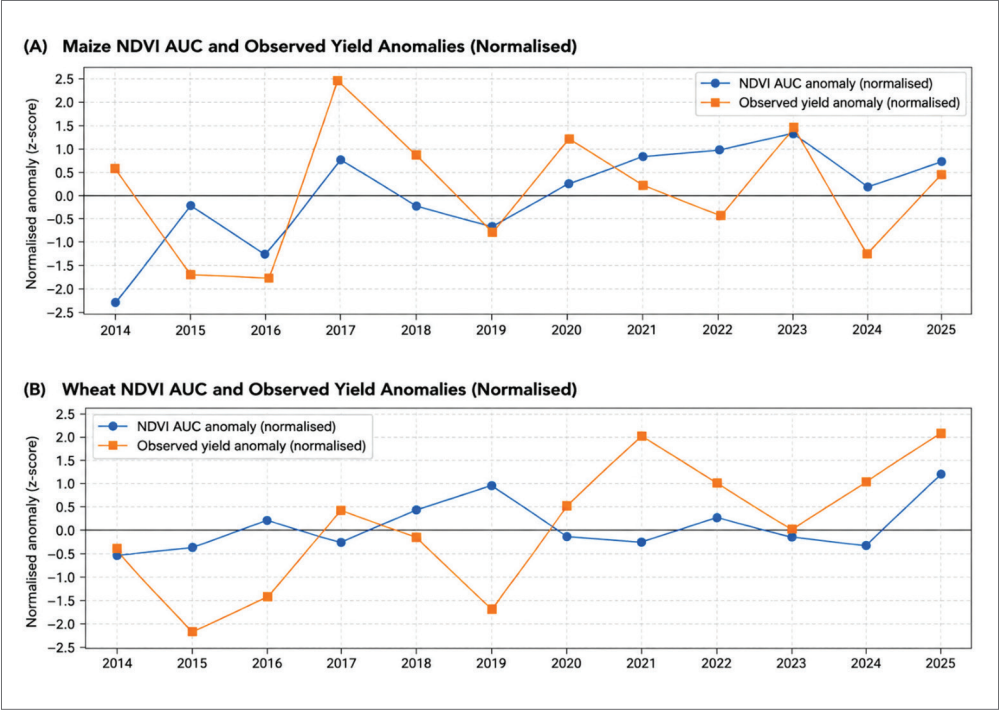


FIGURE 20. Normalised seasonal NDVI AUC and observed crop yield anomalies for (A) maize and (B) wheat in Free State (2014–2025)

7.4 Relationships between climate, vegetation and agricultural production

7.4.1 The preceding analyses described seasonal climate, climate hazards, large-scale climate variability, vegetation dynamics and crop-climate suitability across the Free State. However, they do not quantify the relative contribution of each environmental dataset to variations in crop productivity (t ha^{-1}).

7.4.2 A modelling framework combining PCA and OLS regression was developed separately for maize and wheat. The crops were analysed separately since their growing seasons, climatic requirements and seasonal responses differ.

7.4.3 Predictors were organised into four information domains (referred to as ‘hierarchies’): climate, hazards, ENSO and agriculture, as illustrated in Table 5. PCA was applied independently within each hierarchy, where each stage introduces a new type of information while keeping the best principal components from previous hierarchies. Figure 21 summarises the complete modelling workflow.

TABLE 5. Hierarchical predictor groups used in the PCA and regression analysis

PCA	Information included	Role in the analysis
H1	Climate	Baseline seasonal climatic conditions
H2	Climate + Hazards	Adds seasonal climatic extremes
H3	Climate + Hazards + ENSO	Adds large-scale climate variability
H4	Climate + Hazards + ENSO + Agriculture	Adds vegetation response and climatic suitability

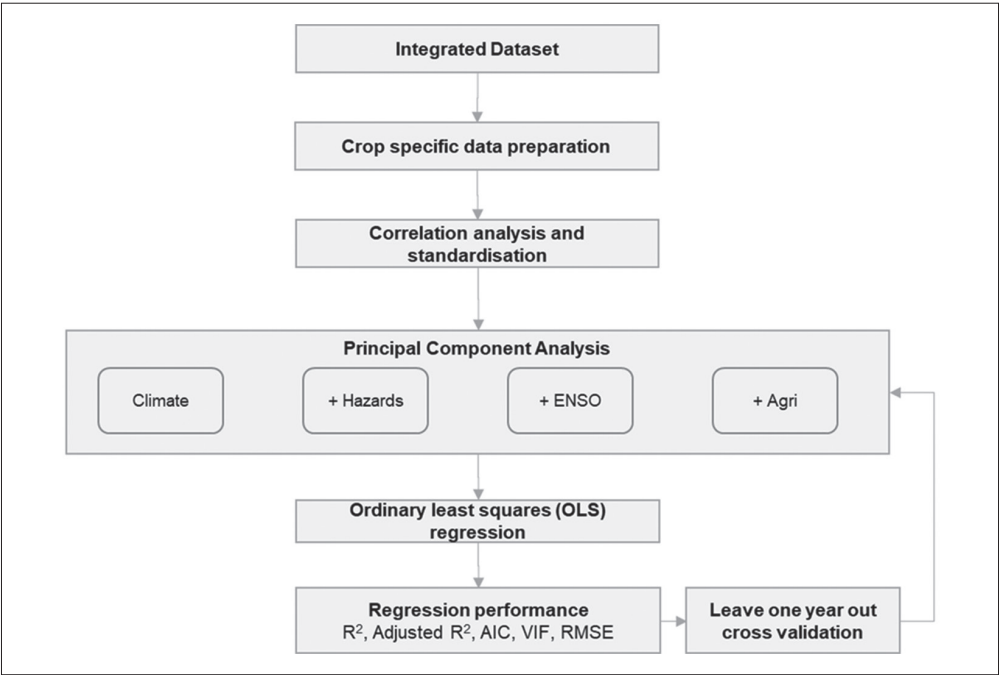


FIGURE 21. Modelling framework used to evaluate the contribution of climate, hazards, ENSO and agricultural indicators to crop productivity

7.4.4 Predictor groups and correlation analysis

7.4.4.1 Exploratory correlation analysis was undertaken to investigate relationships among predictor variables and provincial crop productivity. Correlation coefficients were used to identify linear relationships, and monotonic associations that may not be strictly linear. This analysis was used to understand the structure of the predictor dataset rather than to select variables directly.

7.4.4.2 Strong correlations among many environmental variables confirmed that multicollinearity was likely to influence conventional regression modelling and therefore justified the use of PCA prior to regression. The variables were therefore grouped according to Tables 5 and 6.

TABLE 6. Predictor groups and variables represented in the hierarchical PCA regression framework

Hierarchy	Variables represented	Interpretation
Climate	Seasonal rainfall, temperature, relative humidity, wind, air pressure and related seasonal climate measures	Background climatic conditions during the growing season
Hazards	Drought count, duration and intensity. Heatwave frequency, extreme rainfall intensity, fire-weather and related thermal or hazard indicators	Frequency or severity of adverse seasonal conditions
ENSO	Seasonal mean, maximum and minimum ONI	Large-scale climate variability
Agriculture	Mean NDVI, seasonal peak NDVI duration, NDVI AUC, hazard-adjusted suitability	Vegetation response and climatic favourability

7.4.5 *Grouped principal component analysis*

7.4.5.1 The number of candidate Principle Components (PCs) was constrained to limit the model-search space. The setting is an upper bound: the number of PCs available for a group cannot exceed the number permitted by its variables and observations. Sensitivity testing indicated that a maximum of two candidate PCs provided the more parsimonious maize representation, whereas wheat retained useful information when up to four PCs were considered. These crop-specific limits were treated as a dimensionality sensitivity assumption rather than as a general PCA rule.

7.4.5.2 Rather than performing a single PCA across all environmental variables, separate PCAs were considered for more comprehensive environmental hierarchies representing distinct components of the crop system. Principal components within the same PCA group are orthogonal by construction. Components derived from different groups are not necessarily orthogonal because the PCAs are fitted independently. Residual multicollinearity between domains was therefore assessed within each candidate regression using the Variance Inflation Factor (VIF.) Models exceeding the specified maximum VIF of five did not meet the standard model-selection criteria. Within each hierarchy, principal components were ranked according to the proportion of variance explained. Component scores, explained variance and loading matrices were retained to preserve interpretation of the underlying environmental processes.

7.4.6 *Regression results*

— **Maize regression results:** Table 7 summarises the performance of the four candidate OLS regression models for maize. The progressive inclusion of climate hazards (H2), ENSO (H3) and vegetation response and climatic suitability (H4) generally increased the proportion of interannual variability explained by the regression models while reducing the overall prediction error. Maize model fit improved across the four information hierarchies. The H3 model explained approximately 58% of the observed variation in productivity (adjusted $R^2 = 0.394$). Adding the agriculture hierarchy increased full-sample R^2 to 0.732 and adjusted R^2 to 0.553. Thus, regression performance of the

observed and predicted crop productivity (t ha^{-1}) improved systematically across the four modelling hierarchies (Table 7, Figure 22). The out-of-sample performance of H3 and H4 is assessed in Section 7.4.7.

TABLE 7. In-sample regression statistics across hierarchies for maize

Crop	Model Type	R ²	Adj. R ²	RMSE	MAE	AIC	BIC	Max VIF
Maize	H1	0.222	0.136	0.861	0.734	30.3909	30.9961	1.000
Maize	H2	0.353	0.191	0.786	0.582	25.909	26.817	1.001
Maize	H3	0.576	0.394	0.636	0.457	22.788	23.998	3.139
Maize	H4	0.732	0.553	0.506	0.381	14.329	15.842	4.562

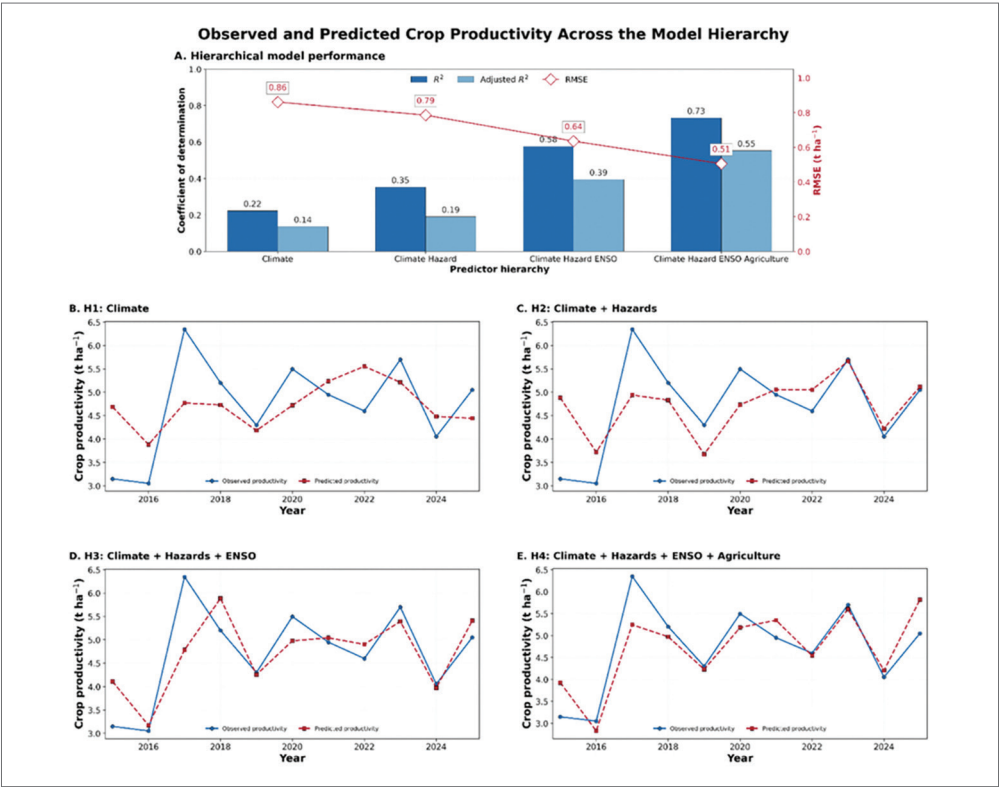


FIGURE 22. Observed and predicted maize productivity across the hierarchical modelling framework: (A) shows fit statistics across H1–H4, (B) to (E) compare observed and predicted productivity as climate, hazards, ENSO and agricultural indicators are progressively incorporated

— **Wheat regression results:** A similar pattern was observed for wheat (Table 8, Figure 23). Climate-only models explained approximately 25% of the observed inter-

annual variability, with successive improvements obtained following the inclusion of climatic hazards, ENSO and agriculture. Wheat showed the same direction of improvement in fitted performance. R^2 increased from 0.674 for H3 to 0.829 for H4, while adjusted R^2 increased from 0.553 to 0.732. The out-of-sample performance of H3 and H4 is assessed in Section 7.4.7.

TABLE 8. In-sample regression statistics across hierarchies for wheat

Crop	Model Type	R^2	Adj. R^2	RMSE	MAE	AIC	BIC	Max VIF
Wheat	H1	0.249	0.174	0.812	0.638	26.799	27.405	1.000
Wheat	H2	0.497	0.386	0.664	0.559	24.579	25.487	1.076
Wheat	H3	0.674	0.553	0.534	0.398	17.477	18.687	1.040
Wheat	H4	0.829	0.732	0.387	0.318	10.575	12.088	2.882

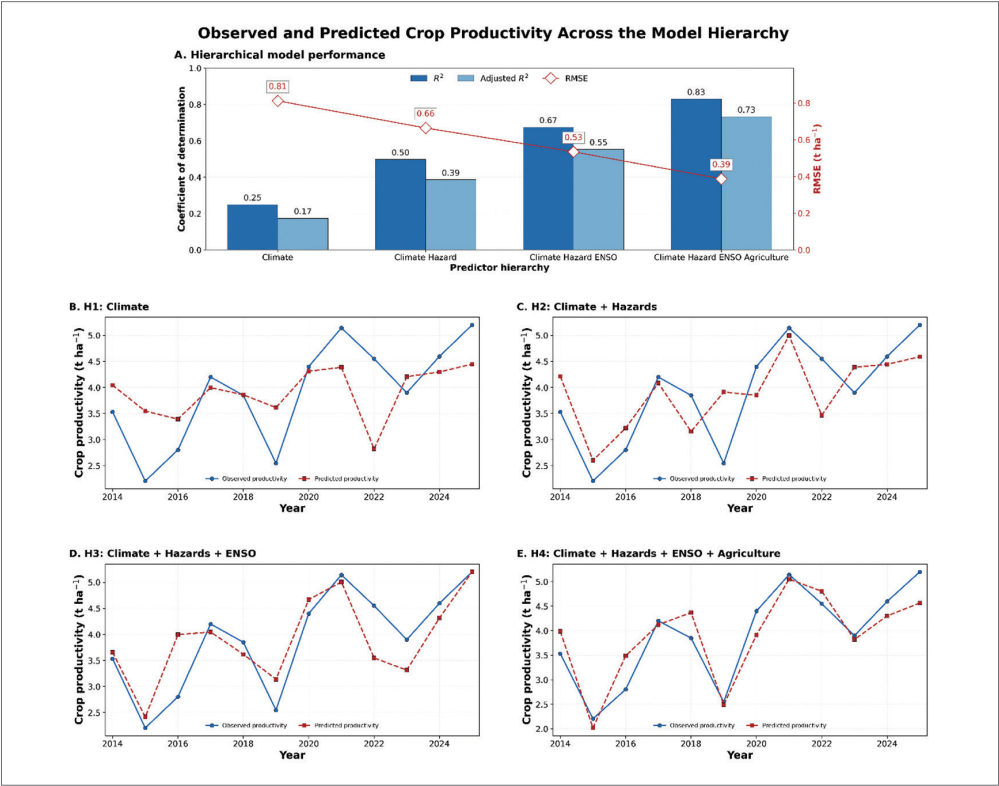


FIGURE 23. Observed and predicted wheat productivity across the hierarchical modelling framework: (A) shows fit statistics across H1–H4, (B) to (E) compare observed and predicted productivity as climate, hazards, ENSO and agricultural indicators are progressively incorporated

7.4.7 Model validation

7.4.7.1 Given the small annual sample and the number of candidate PCA-regression specifications, LOYO cross-validation was used to assess whether the H3 and H4 results were retained outside the observations used for estimation. Two complementary procedures were applied.

7.4.7.2 Fixed-structure LOYO assessed the final selected model specification. One year was removed at a time, standardisation and PCA were refitted on the remaining years, and the held-out year was projected into the training PCA solution before prediction. The selected component positions were retained, although their scores and loadings were re-estimated from the training sample.

7.4.7.3 Nested LOYO assessed the complete modelling procedure. For each held-out year, standardisation, PCA and candidate-model selection were repeated using the training years only. The model selected within that fold was then used to predict the excluded observation. Neither the PCA solution nor the selected regression specification was therefore informed by the held-out year.

7.4.7.4 Validation was summarised using cross-validated R^2 , RMSE, MAE and bias. Full-sample R^2 and RMSE are shown alongside the LOYO results to make the change from fitted to out-of-sample performance explicit. The difference between full-sample and fixed-structure LOYO R^2 was reported as a generalisation gap. LOYO was used to assess evidence of generalisation rather than as a binary test proving the absence of overfitting.

TABLE 9. Full-sample and LOYO performance of model

Crop	Hierarchy	Fit R^2	Fit RMSE	Fit MAE	LOYO R^2	LOYO RMSE	LOYO MAE	R^2 gap
Maize	H3	0.576	0.636	0.457	0.245	0.885	0.806	0.331
Maize	H4	0.732	0.506	0.381	0.532	0.697	0.587	0.200
Wheat	H3	0.675	0.534	0.398	0.351	0.729	0.524	0.324
Wheat	H4	0.829	0.387	0.318	0.665	0.527	0.438	0.164

7.4.7.5 For maize, the inclusion of the H4 improved both fitted and cross-validated performance. Fitted R^2 increased from 0.576 for H3 to 0.732 for H4, while LOYO R^2 increased from 0.245 to 0.532. Cross-validated RMSE decreased from 0.885 to 0.697 t ha⁻¹ and MAE from 0.806 to 0.587 t ha⁻¹. The R^2 generalisation gap declined slightly from H3 (0.331) to H4 (0.2), indicating that the improvement in fitted performance was accompanied by a corresponding improvement in held-out predictions rather than a substantial increase in the difference between fitted and out-of-sample performance.

7.4.7.6 Wheat showed a stronger improvement following the inclusion of the H4. Fitted R^2 increased from 0.675 for H3 to 0.829 for H4, while LOYO R^2 increased from 0.351 to 0.665. Cross-validated RMSE decreased from 0.729 to 0.527 t ha⁻¹ and MAE from 0.524 to 0.438 t ha⁻¹. The generalisation gap also decreased from 0.324 to 0.164, indicating

that the H4 wheat model retained a greater proportion of its fitted explanatory performance when applied to held-out years.

7.4.7.7 LOYO R^2 remained positive for both crops and both hierarchies, although performance was consistently lower than that obtained from the fitted models. This reduction is expected when predictions are generated for observations excluded from model estimation. Importantly, the addition of the H4 improved LOYO R^2 and reduced prediction error for both maize and wheat. The H4 improvement was therefore not limited to in-sample model fit.

7.4.8 Regression conclusion

7.4.8.1 For both crops, fitted performance increased as additional information domains were introduced. Climate-only models provided the baseline, with further improvements after the inclusion of hazards and ENSO. The highest fitted performance was obtained after adding the H4, which contains vegetation and suitability information. The final models were statistically significant overall ($p < 0.05$, F-test), indicating that the included predictors were jointly associated with variation in crop productivity.

7.4.8.2 Observed-versus-predicted comparisons showed that the fitted models captured much of the observed interannual variation in crop productivity. Some differences between observed and predicted productivity remained, which may reflect factors not represented in the environmental datasets, including agricultural management, cultivar selection, pests and disease. Given the limited annual sample, the fitted models alone were not considered sufficient evidence of model generalisability.

7.4.8.3 These findings do not establish that each predictor domain has a unique or causal effect on productivity. Statistical significance of the overall model indicates a joint relationship between the included predictors and productivity rather than an independent contribution from each information domain. The hierarchy shows how model fit and validation performance change as additional environmental information is introduced.

7.5 Loss distribution shifts

Beyond explaining average crop productivity, the analytical framework provides insights into how the distribution of agricultural yield losses has shifted over time. This is a critical consideration for financial institutions managing agricultural credit and insurance portfolios. To investigate these distributional shifts, the study period was divided into an early period (2014–2019) and a late period (2020–2025), with the split selected to balance sample sizes while capturing recent climate trends and ENSO events including the 2020–2022 La Niña and 2023–2024 El Niño episodes.

7.6 Shifts in productivity distributions

7.6.1 For maize, the mean productivity declined from 4.98 t ha⁻¹ in the early period to 4.65 t ha⁻¹ in the late period (6.6% reduction), while the coefficient of variation

increased from 0.27 to 0.38 (40.7% increase). Wheat showed a similar pattern, with mean productivity declining from 3.78 to 3.38 t ha⁻¹ (10.6% reduction) and the coefficient of variation increasing from 0.29 to 0.42 (44.8% increase). The observed minimum also declined for both crops, from 3.05 to 2.22 t ha⁻¹ for maize and from 2.21 to 1.42 t ha⁻¹ for wheat.

7.6.2 These results indicate lower average productivity and greater interannual variability in the later period. The distributional comparison provides some evidence of a shift for maize using the Kolmogorov-Smirnov test (KS = 0.667, $p = 0.04$), while the evidence for wheat is weaker at the 5% significance level (KS = 0.600, $p = 0.08$), given the small number of annual observations.

7.7 Frequency of adverse productivity outcomes

7.7.1 To examine whether the distributional changes correspond to a greater frequency of adverse agricultural outcomes, productivity was compared with thresholds defined relative to the early-period mean. These thresholds are used as indicators of low-productivity seasons rather than estimates of financial loss or credit default.

7.7.2 Using a threshold of 70% of the early-period mean, the frequency of low-productivity seasons increased from 12.5% to 28.6% for maize and from 20.0% to 28.6% for wheat. At an 80% threshold, the corresponding frequencies increased from 25.0% to 42.9% for maize and from 40.0% to 57.1% for wheat. The results therefore indicate a greater occurrence of below-average productivity outcomes in the later period, although the small number of annual observations limits inference about changes in the underlying probability distribution.

7.7.3 The threshold analysis considers productivity in isolation and does not attribute individual loss years to specific drivers. The wider modelling framework provides this additional context by relating productivity to climate, hazards, ENSO, suitability and vegetation response. This creates a basis for identifying the environmental conditions associated with adverse productivity outcomes and, where agricultural financial information is available, for subsequently examining how these conditions may translate into financial risk.

8. DISCUSSION

The modelling results demonstrate the value of integrating multiple environmental datasets within a single analytical framework. From an actuarial and risk management perspective, the framework enables agricultural productivity to be linked directly to measurable environmental drivers, providing a granular basis for understanding climate-related production variability.

8.1 Interpretation of the findings

8.1.1 The proposed methodology combined multiple sources of information in a common analytical framework operating at the spatial resolution of the NDVI observations.

8.1.2 The results demonstrate that agricultural production within the Free State is influenced by the cumulative interaction of large-scale climate variability, seasonal meteorological conditions and vegetation response rather than by any single climatic variable. ENSO influences regional atmospheric circulation, altering seasonal rainfall and temperature patterns, which subsequently affect drought development, vegetation growth and ultimately agricultural productivity. The observed relationships highlight the importance of considering climate variability as a cascading process rather than a sequence of isolated environmental variables.

8.1.3 The progressive integration of climate, hazard and vegetation datasets also illustrates that satellite observations provide valuable information beyond that contained within conventional meteorological records. While rainfall and temperature describe the environmental conditions experienced by crops, NDVI captures the realised biological response of vegetation to those conditions. Vegetation indices act as an important intermediary between climate forcing and agricultural production.

8.2 Climate variability and agricultural production

8.2.1 The analysis confirms the dominant influence of rainfall variability on cereal production within the Free State. Seasonal precipitation remains the principal determinant of crop water availability, particularly for rain-fed production systems that dominate much of the province.

8.2.2 Although long-term rainfall trends were comparatively modest, substantial interannual variability was observed throughout the study period. This finding suggests that increasing production risk is likely to arise from greater climatic variability and the occurrence of extreme events rather than gradual reductions in average rainfall alone.

8.2.3 In contrast, temperatures exhibited a more consistent warming trend. Increasing temperatures influence agricultural production through several mechanisms, including increased evapotranspiration, accelerated crop development, shortened grain-filling periods and elevated heat stress during sensitive reproductive growth stages. These effects are particularly important when high temperatures coincide with below-average rainfall, amplifying drought impacts through increased atmospheric moisture demand.

8.2.4 The combination of relatively stable rainfall totals with progressively increasing temperatures suggests that future agricultural production may become increasingly constrained by water availability, even in the absence of substantial changes in annual precipitation.

8.3 The role of agricultural hazards

8.3.1 The hazard analyses demonstrated that agricultural risk is not adequately represented by average climatic conditions alone. Drought, heatwaves, wildfire danger and extreme rainfall each influence crop production through distinct mechanisms, and their occurrence frequently reflects the interaction of multiple climatic variables.

8.3.2 Among the hazards considered, drought exhibited the strongest and most persistent relationship with vegetation stress. Prolonged rainfall deficits reduced soil moisture availability, resulting in lower NDVI values and reduced seasonal vegetation productivity. The association between severe drought periods and strong El Niño events further illustrates the influence of large-scale climate variability on agricultural systems.

8.3.3 Heatwave occurrence increased throughout the study period, consistent with the observed warming trend. While elevated temperatures alone do not necessarily reduce crop yields, prolonged periods of extreme heat during flowering or grain filling may substantially reduce productivity through increased physiological stress.

8.3.4 Fire-weather conditions displayed considerable temporal variability but generally occurred during years characterised by elevated temperatures and below-average rainfall. Although wildfire represents a relatively localised hazard compared with drought, its inclusion within the analytical framework provides a more comprehensive assessment of environmental conditions affecting agricultural systems.

8.3.5 Flood hazard exhibited a distinctly different temporal behaviour, with elevated flood potential occurring predominantly during wetter La Niña years. This inverse relationship with drought demonstrates the importance of considering multiple hazards simultaneously rather than assessing each independently.

8.4 Value of satellite-derived vegetation monitoring

8.4.1 One of the principal strengths of the proposed framework is the integration of satellite-derived NDVI and EO data with climatic and hazard information.

8.4.2 Remote sensing provides objective, spatially continuous observations of vegetation conditions that cannot be obtained through conventional field surveys at provincial scales. By restricting the analysis to agricultural land identified harvested areas, the vegetation analyses specifically represent crop growth rather than surrounding natural vegetation.

8.4.3 The application of Savitzky-Golay smoothing produced temporally consistent vegetation trajectories while preserving the seasonal characteristics associated with crop development. Derived metrics such as peak NDVI, integrated vegetation growth (NDVI AUC) and vegetation anomalies provided quantitative measures of seasonal crop performance that could be compared directly with climatic conditions.

8.4.4 Vegetation indices should not be interpreted as replacements for climate variables but rather as complementary indicators describing the realised response of crops to environmental conditions. Integrating NDVI with climate and hazard variables provides a more comprehensive and granular assessment than analysing either dataset independently.

8.5 Crop suitability assessment

8.5.1 The suitability analyses demonstrated that climatic suitability varies both spatially and temporally throughout the Free State, with generally more favourable

conditions in the wetter eastern production regions and lower suitability towards the drier west. The FAO limiting-factor approach produced lower suitability estimates, as the overall score was determined by the least favourable climatic condition. Low suitability should not, however, be interpreted as indicating that crop production is infeasible, since management practices such as irrigation, cultivar selection and planting decisions can compensate for climatic limitations.

8.5.2 This distinction is particularly relevant for agricultural risk assessment. A region experiencing optimal temperatures, but insufficient rainfall remains unsuitable for production despite favourable thermal conditions. Conversely, adequate rainfall cannot fully compensate for extreme temperatures during critical growth stages. Furthermore, climatic suitability describes rainfall and temperature conditions over the crop-growing season but does not capture the occurrence or timing of individual weather hazards. This distinction is important because similar seasonal rainfall and temperature conditions may coincide with different levels of drought, heatwave, extreme rainfall or fire-weather exposure. Hazard effects may also persist beyond the period in which they occur, meaning that their influence on crop development may not be fully represented by seasonal climate averages.

8.5.3 The hazard-adjusted suitability measure was introduced to incorporate this additional information by applying penalties for hazards occurring during the growing season. It should therefore not be interpreted as an empirically superior alternative to the FAO-based climatic suitability measure. Rather, it provides an additional representation of seasonal growing conditions in which both climatic favourability and realised hazard occurrence are considered. Although suitability indices are inherently simplified representations of crop growth, they provide a useful framework for evaluating the potential impacts of future climatic variability on agricultural production.

8.6 Applications to banking and insurance

8.6.1 The analytical framework developed in this study has applications extending beyond agricultural monitoring. For banks and financial institutions, agricultural production directly influences the risk and repayment capacity of farming enterprises. Reduced yields resulting from climatic variability may therefore increase both the probability of default (PD) and potential loss given default (LGD) within agricultural lending portfolios. The spatially explicit nature of the framework allows climate exposure to be evaluated at individual farming regions rather than broader aggregated areas, providing a more detailed understanding of portfolio vulnerability.

8.6.2 Within insurance, the framework provides objective indicators of hazard occurrence and vegetation conditions that may support underwriting, portfolio monitoring and claims assessment. Satellite-derived vegetation indices also offer potential for developing parametric insurance products where payouts are triggered by objectively observed environmental conditions rather than traditional loss adjustment.

8.6.3 The impacts of climate variability, agricultural hazards and ENSO cycles highlight the need for financial institutions to revisit assumptions around correlation risk on agricultural portfolios. Historically independent production regions may become more correlated under widespread drought or heat stress. This is exacerbated by the findings from the ONI trajectory analysis in Section 6.1, which suggests a stronger 2026 El Niño development and hence potentially greater correlation risk under extreme drought conditions.

8.6.4 The quantification of loss distribution shifts in Sections 7.6 and 7.7 provides additional granularity for these risk assessments. The observed decrease in average productivity and increase in the probability of severe loss events translate into higher expected credit losses and greater tail risk for agricultural portfolios. For banks, this implies that historical default rates and loss given default assumptions may understate current risk exposures, potentially calling for recalibration of internal ratings, provisioning models and capital allocation. For insurers, the widening distribution of productivity outcomes suggests that premium rates based on historical loss experience may no longer be adequate, particularly for products covering extreme events such as drought or multi-peril crop failure.

8.6.5 The methodology may similarly support enterprise climate risk assessments, physical climate stress testing and regulatory reporting by providing quantitative measures linking physical hazards with potential agricultural impacts.

8.6.6 The framework may also be viewed in the context of broader actuarial initiatives aimed at monitoring and quantifying climate risk in South Africa, including the ASSA Climate Index (ACI) (2025). The ACI provides a standardised measure of changes in climate extremes relative to a historical reference period, using percentile-based thresholds to identify unusually severe conditions. This is well suited to monitoring changes in the frequency and intensity of climate extremes. However, it does not by itself indicate how those conditions translate into impacts on a particular crop, location or growing season. It also means that detected events are comparable only to the reference climatology, not directly to each other across time. The present study complements the ACI by focusing specifically on the transmission of climate variability and extremes into agricultural production risk, using fixed, regionally calibrated hazard thresholds that maintain temporal consistency and direct comparability across events. The inclusion of EO data, crop calendars and spatial agricultural exposure could also inform future sector-specific extensions of the ACI, particularly where the objective is to move from identifying climate anomalies towards assessing their potential impacts.

8.7 Methodological contributions

8.7.1 A significant contribution of this study lies in the spatial harmonisation methodology developed to integrate datasets with substantially different spatial resolutions. Rather than interpolating all datasets onto a common grid, the analysis adopted the NDVI

grid as the computational framework. Climate variables, hazard metrics and suitability indices were allocated to each NDVI cell using spatial joins, allowing high-resolution vegetation observations to be analysed alongside broader climatic information whilst preserving the inherent characteristics of each dataset.

8.7.2 This approach minimises unnecessary interpolation, reduces computational complexity and provides a flexible analytical framework that is readily transferable to other agricultural regions. Taken together, these methodological features extend beyond the development of an agricultural risk model and provide an actuarial framework for climate-informed decision-making. The framework also aligns with the principles of the Actuarial Control Cycle (Bellis et al., 2010). It supports problem definition by identifying the key drivers of agricultural climate risk, can inform decisions on pricing, underwriting and capital assessment, and enables ongoing monitoring and model refinement as new data become available. In doing so, it provides a practical actuarial framework for managing physical climate risk.

8.8 Limitations

8.8.1 Several limitations should be acknowledged when interpreting the results. The harvested-area datasets represent modelled agricultural distributions rather than annually observed crop locations. Consequently, temporal changes in planting patterns throughout the study period are not explicitly represented.

8.8.2 Secondly, although NDVI provides an effective measure of vegetation greenness, it does not directly measure crop yield. Vegetation indices may saturate under dense canopy conditions and cannot distinguish between crop species where multiple crops exhibit similar spectral characteristics.

8.8.3 Thirdly, the climate datasets operate at substantially coarser spatial resolution than the satellite observations. Although the harmonisation methodology preserves native climate information, local-scale climatic variability occurring below the resolution of the climate grids is not explicitly represented.

8.8.4 Finally, the regression analyses describe statistical relationships between climatic variables and agricultural production but should not be interpreted as establishing direct causal mechanisms. Agricultural production is also influenced by numerous management factors, including cultivar selection, fertiliser application, irrigation practices, pest pressure and technological improvements that were beyond the scope of this study.

8.9 Future research

8.9.1 The framework developed in this study provides several opportunities for future development. Future research could incorporate additional EO products describing evapotranspiration, soil moisture, land surface temperature and photosynthetically active radiation to provide a more comprehensive representation of crop growth processes.

8.9.2 Machine learning approaches, including random forests, gradient

boosting and Bayesian hierarchical models, may also improve predictive performance while accommodating complex non-linear interactions between climatic variables.

8.9.4 The methodology could further be extended to incorporate future climate projections from global climate models, enabling assessments of changing agricultural suitability under varying emissions scenarios. Such analyses would support long-term adaptation planning, agricultural investment decisions and climate stress testing exercises within the financial sector.

8.9.5 Financial institutions could produce granular risk metrics and outcomes, such as portfolio-adjusted PDs, LGDs, provisions and capital requirements by supplementing this analysis with internal risk and financial data. This would allow for greater physical risk vulnerability assessments, potential portfolio restructuring and opportunities to support clients in managing climate risk.

9. CONCLUSION

9.1 This study developed a geospatial modelling framework to assess the relationships between climate observations, hazard indicators, ENSO, vegetation response, and maize and wheat productivity in the Free State. Climate and EO data were analysed within crop-specific growing seasons, allowing the different responses of summer maize and winter wheat to be considered separately.

9.2 The methodology successfully harmonised multiple datasets operating at different spatial and temporal resolutions into a unified analytical framework centred on high-resolution NDVI observations. The resulting workflow enabled climatic variability, environmental hazards and vegetation dynamics to be evaluated consistently across the maize- and wheat-producing regions of the Free State.

9.3 The results show spatial and temporal differences in agricultural growing conditions across the province. Through the hierarchical modelling structure, the findings demonstrate that the additional sources of environmental information improve the explanation of interannual crop productivity. The productivity analysis also identified lower mean productivity and greater interannual variability in the later assessment period, together with a higher observed frequency of low-productivity seasons. Overall, the results show that agricultural production risk cannot be characterised from a single climate indicator or annual yield series alone, but through a combination of environmental drivers.

9.4 Beyond its application to agricultural monitoring, the framework provides a scalable methodology suitable for climate risk assessments within banking, insurance and broader financial risk management. The modular nature of the workflow, combined with its reliance on globally available satellite datasets, facilitates application across different regions, crop types and climatic conditions.

9.5 As climate variability continues to influence agricultural systems worldwide, integrated geospatial approaches such as those presented in this study will become increasingly important for supporting evidence-based decision-making, improving climate resilience and enhancing the quantitative assessment of physical climate risk.

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APPENDIX A

A.1 Climate data processing

A.1.1 Daily climate variables were obtained from the ERA5 reanalysis climate datasets covering the period 1990–2025. The climate datasets possess grid resolutions of approximately 31 km. The following variables were extracted:

- precipitation;
- maximum temperature;
- mean temperature;
- wind speed;
- relative humidity; and
- air pressure.

A.1.2 As the source datasets contain regular latitude-longitude grids, daily observations were aggregated without interpolation. Spatial averaging was subsequently performed only where provincial or combined crop region summary statistics were required.

A.1.3 Accumulation variables, including precipitation, were summed throughout the growing season, while state variables including temperature, relative humidity, air pressure and wind speed were averaged. Seasonal maxima and minima were additionally retained for selected variables, such as maximum and minimum air temperature.

A.1.4 Monthly and annual climatologies were subsequently calculated to characterise long-term seasonal variability. Seasonal climate variables were initially calculated independently for each climate grid cell. Provincial and combined crop region values were subsequently obtained by averaging the seasonal values across all climate cells located within the respective region.

A.2 ENSO characterisation

A.2.1 Large-scale climate variability was represented using the ONI, which describes sea surface temperature anomalies within the equatorial Pacific Ocean. Monthly ONI values were classified according to the National Oceanic and Atmospheric Administration (NOAA) categories in Table 10. Furthermore, ONI values should be lagged by assessing the correlation of lagged cycles with hazard intensifications.

A.2.2 These classifications were used to investigate the influence of ENSO variability on regional climate conditions and vegetation dynamics.

TABLE 10. Classification of ENSO conditions according to ONI magnitude

ENSO category	ONI (°C)
Strong La Niña	≤ -1.5
Moderate La Niña	-1.4 to -1.0
Weak La Niña	-0.9 to -0.5
Neutral	-0.4 to $+0.4$
Weak El Niño	$+0.5$ to $+0.9$
Moderate El Niño	$+1.0$ to $+1.4$
Strong El Niño	$+1.5$ to $+1.9$
Very Strong El Niño	$\geq +2.0$

A.3 Drought

A.3.1 Meteorological drought was characterised using the k -month Standardised Precipitation Index ($SPI_t^{(k)}$) (McKee et al., 1993), which quantifies precipitation anomalies over a rolling t -month accumulation period. Monthly precipitation totals were first calculated for each climate grid cell before cumulative k -month precipitation totals were derived as:

$$P_t^{(k)} = \sum_{i=t-k+1}^t R_i$$

where:

- t is the month at which the accumulation period ends;
- k is the number of months over which precipitation is accumulated;
- R_i is precipitation during month i ; and
- $P_t^{(k)}$ is accumulated precipitation over the k -month period ending in month t .

A.3.2 A gamma probability distribution was fitted to the non-zero t -month precipitation totals for each climate grid cell. The cumulative probability of precipitation was calculated as:

$$H_k(P_t^{(k)}) = q + (1 - q)G(P_t^{(k)})$$

where:

- $G(P_t^{(k)})$ is the cumulative gamma distribution;
- q is the probability of zero precipitation; and
- H_k is the fitted cumulative probability distribution for precipitation accumulated over scale k .

A.3.3 The cumulative probability was transformed to the standard normal distribution to obtain $SPI_t^{(k)}$:

$$SPI_t^{(k)} = \Phi^{-1}\left[H_k\left(P_t^{(k)}\right)\right]$$

where:
— Φ^{-1} denotes the inverse cumulative distribution function of the standard normal distribution.

A.3.4 Negative $SPI_t^{(k)}$ values indicate below-average precipitation, with increasingly negative values representing greater drought severity. Drought severity was classified according to the World Meteorological Organization (WMO, 2012) thresholds shown in Table 11.

TABLE 11. SPI classification thresholds used to characterise precipitation conditions

$SPI_t^{(k)}$ value	Classification
≥ 2.0	Extremely wet
1.5 to 1.99	Severely wet
1.0 to 1.49	Moderately wet
−0.99 to 0.99	Near normal
−1.0 to −1.49	Moderately dry
−1.5 to −1.99	Severely dry
≤ -2.0	Extremely dry

A.4 Heatwaves

A.4.1 Heatwaves were identified using a percentile-based threshold approach. For each climate grid cell, the daily maximum temperature (T_{max}) was compared with the climatological 90th percentile (T_{90}) calculated over a 30-year reference period. A heatwave day was defined as

$$I_t = \begin{cases} 1, & T_{max,t} > T_{90,t} \\ 0, & \text{otherwise} \end{cases}$$

where:
— $T_{max,t}$ is the daily maximum temperature on day t ;
— $T_{90,t}$ is the corresponding 90th percentile threshold; and
— I_t is the heatwave indicator.

A.4.2 A heatwave event was defined as three or more consecutive heatwave days. Seasonal heatwave exposure was quantified as

$$H = \sum_{t=1}^N I_t$$

where:

- H is the total number of heatwave days during the crop growing season; and
- N is the number of days within the growing season.

A.5 Extreme rainfall

A.5.1 Extreme rainfall was characterised using a percentile-based threshold approach. A day was classified as experiencing extreme rainfall when daily precipitation exceeded the climatological 95th percentile calculated independently for each climate grid cell:

$$I_t = \begin{cases} 1, & R_t > P_{95} \\ 0, & \text{otherwise} \end{cases}$$

where:

- R_t is the daily precipitation and P_{95} is the corresponding grid-cell-specific 95th percentile threshold.

A.5.2 Seasonal extreme rainfall frequency was calculated as:

$$N_{ER} = \sum_{t=1}^n I_t$$

where:

- N_{ER} is the number of extreme rainfall days during the growing season, and n is the number of days.

A.5.3 Seasonal rainfall associated with extreme events was calculated as:

$$R_{ER} = \sum_{t=1}^n R_t I_t$$

where:

- R_{ER} is the cumulative rainfall occurring on extreme rainfall days.

A.6 Fire weather

A.6.1 Fire-weather conditions were represented using a custom daily proxy (FWP) combining atmospheric heat, wind, humidity and recent rainfall conditions. The proxy was designed to identify days when the meteorological environment was comparatively favourable for vegetation and fuel drying and fire spread.

A.6.2 Higher proxy values represent hotter, windier and drier conditions

together with lower antecedent rainfall and longer periods since meaningful rainfall. As the proxy is a relative standardised index, it does not correspond directly to operational fire danger categories.

A.6.3 High fire-weather days were defined as days exceeding the 90th percentile (P_{90}) of the historical proxy distribution, while extreme fire-weather days exceeded the 95th percentile (P_{95}).

A.6.4 Seasonal exposure was calculated as the total number of days exceeding each threshold.

TABLE 12. Fire-weather classification thresholds

Category	Threshold
Normal fire-weather conditions	$(FWP) < (P_{90})$
High fire-weather conditions	$(P_{90}) \leq (FWP) < (P_{95})$
Extreme fire-weather conditions	$(FWP) \geq (P_{90})$

A.7 NDVI processing

A.7.1 Satellite-derived vegetation observations were obtained from the Copernicus Global Land Service NDVI dataset at a spatial resolution of 300 m. The dataset is provided as atmospherically corrected composites with cloud contamination minimised during product generation; consequently, no additional cloud masking was applied.

A.7.2 To reduce residual temporal noise while preserving seasonal vegetation dynamics, the NDVI time series was smoothed using a Savitzky–Golay (SG) filter. The SG filter applies a local polynomial regression within a moving temporal window, reducing short-term fluctuations while preserving the timing and magnitude of seasonal vegetation peaks and senescence. This approach is widely used in agricultural remote sensing because it maintains phenological characteristics more effectively than simple moving-average smoothing.

A.7.3 The NDVI grid was spatially intersected with the combined crop region. Each retained NDVI grid cell was assigned a unique identifier, creating a permanent spatial lookup table linking vegetation observations to agricultural land. The lookup table was subsequently joined to the complete NDVI time series.

A.7.4 NDVI observations were grouped according to the crop growing seasons defined in Section 5.3. Maize observations were aggregated over the October–May growing season and assigned to the harvest year, whereas wheat observations were aggregated over the May–October growing season.

A.7.5 Unlike mean or peak NDVI, which describe vegetation condition at a single point or average state, NDVI AUC accounts for both the magnitude and duration of vegetation growth. The seasonal NDVI AUC was calculated using the trapezoidal rule:

$$AUC = \sum_{i=1}^{n-1} \frac{NDVI_i + NDVI_{i+1}}{2} (t_{i+1} - t_i)$$

where:

- AUC is the cumulative seasonal vegetation development;
- $NDVI_i$ is the smoothed NDVI value at observation i ;
- t_i is the observation time; and
- n is the total number of NDVI observations during the crop growing season.