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Statistical Modelling Relevance and Implications for Agricultural Extension

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ABSTRACT

Agricultural extension systems in South Africa face increasing pressure to provide timely, location-specific, and risk-aware advisories to dryland grain farmers under intensifying climate variability. Statistical climate modelling has emerged as a critical bridge between climate science and farm-level decision-making, yet its application within extension practice remains uneven. This review synthesises peer-reviewed literature published between 2010 and 2026 on climate data curation, statistical and spatial modelling, and crop–climate integration relevant to agricultural extension in South Africa and comparable semi-arid regions. Trends in climate variability affecting dryland grain systems are examined alongside statistical methods used to link climate drivers with yield and risk outcomes. Approaches for embedding modelling outputs into extension advisory systems are assessed. Results indicate a shift from descriptive analyses towards integrated, multi-model decision-support frameworks combining downscaled climate data, regression and time-series techniques, and process-based crop models. Persistent gaps remain in local calibration, uncertainty communication, and extension capacity. A consolidated, extension-oriented modelling framework is proposed, with priorities for research, policy, and capacity development identified to strengthen climate-smart agricultural extension.

1. Introduction

Climate change has emerged as one of the most significant challenges facing agricultural systems globally, with disproportionate impacts on rainfed and dryland production systems. In South Africa, dryland grain production—particularly maize, sorghum and legumes—forms the backbone of national food security and rural livelihoods, yet it operates within highly variable summer rainfall environments that are increasingly exposed to heat stress, erratic rainfall and extreme events (Archer et al., 2010; Lobell et al., 2011). These climatic pressures directly influence planting decisions, cultivar choice, input allocation and yield stability, especially for smallholder and resource constrained farmers. Agricultural extension services therefore play a critical role in mediating climate risk by translating scientific climate information into actionable, farm level advice.

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2. Literature review

Climate information is inherently complex. It is often probabilistic rather than deterministic, expressed through anomalies, indices, confidence intervals and scenario ranges that are difficult for non-specialists to interpret (Hansen et al., 2011; Meza et al., 2020). Extension officers are required to interpret seasonal forecasts, long term projections and historical climate variability while simultaneously advising farmers on agronomic practices. Without appropriate analytical frameworks, this complexity can lead to misinterpretation, loss of credibility and low uptake of climate informed advisories. Statistical climate modelling provides a means of simplifying and contextualising climate information by identifying key drivers, quantifying risk relationships, and generating decision relevant indicators such as planting windows, drought probabilities and yield distributions. Historically, agricultural modelling systems have evolved from descriptive and experimental approaches towards increasingly integrated decision support tools. Early systems relied heavily on empirical relationships derived from field trials and historical averages, which provided valuable baseline guidance but were poorly suited to non-stationary climate conditions (Dixon et al., 2011). Subsequent advances saw the development of process-based crop models such as DSSAT, APSIM and AquaCrop, which simulate crop growth based on soil, weather, and management processes. While these models offer physiological realism, they are data intensive, sensitive to parameterisation and often underutilised within routine extension due to limited calibration and technical capacity (Thornton & Herrero, 2014; Walker & Schulze, 2012). In parallel, statistical, and econometric models have been widely applied to analyse climate–yield relationships, assess trends and evaluate forecast skill. Regression, time series and spatial models have proved particularly useful for analysing historical climate variability and linking it to observed production outcomes at regional scales (Hewitson & Crane, 2012; Bhebhe et al., 2021). Nevertheless, many earlier applications were designed primarily for research or policy analysis, with limited attention to extension usability, uncertainty communication and feedback from farmers. As a result, modelling outputs often remained disconnected from day-to-day advisory practice. Under conditions of accelerating climate change, the limitations of isolated or poorly calibrated modelling systems become increasingly evident. Dryland grain production systems are especially sensitive to intra seasonal rainfall distribution, temperature extremes during flowering and the frequency of dry spells rather than seasonal means alone (Sultan & Gaetani, 2016). Climate models, when statistically downscaled and locally calibrated, provide a basis for translating these complex dynamics into practical risk management guidance. Integrating statistical climate models with process-based crop models further enhances their relevance by linking climate signals directly to agronomic outcomes, thus supporting climate smart agricultural extension. The aim of this review is to synthesise and critically evaluate literature from 2010 to 2026 on statistical climate modelling approaches relevant to agricultural extension, with a specific focus on dryland grain production in South Africa. The review seeks to:

i. examine how complex climate information has been analysed and simplified for extension use;
ii. assess the strengths and limitations of existing agricultural and climate modelling systems; and
iii. identify pathways for integrating calibrated statistical and crop models into extension decision support frameworks.

By doing so, the review contributes to strengthening evidence based, climate informed agricultural extension capable of supporting resilient dryland grain systems under increasing climatic uncertainty.

3. Methods

3.1 Study design and scope

This study employed a critical narrative review to synthesise literature published between 2010 and 2026 on statistical climate modelling approaches relevant to agricultural extension and decision support, with a specific focus on dryland grain production systems in South Africa. The review targeted studies operating at the interface of climate analysis, crop modelling, and advisory system development, consistent with the systems oriented and applied scope of Agricultural Systems.

The study addressed three analytical objectives:

i. to examine how complex climate information has been analysed and simplified for extension use;

ii. to assess the strengths and limitations of statistical climate models and process-based crop models applied to dryland systems; and

iii. to identify pathways for integrating calibrated statistical and crop models into extension-oriented decision support frameworks.

3.2 Data search strategy

Peer reviewed literature was identified through structured searches in Web of Science, Scopus, ScienceDirect, SpringerLink, Taylor & Francis, and Frontiers databases. To capture applied modelling and extension relevant work that is often underrepresented in indexed journals, additional sources included CGIAR/CCAFS technical reports, FAO publications, and doctoral theses from South African universities.

Search strings combined climate science, modelling, and extension terms, including combinations of statistical climate modelling, climate downscaling, crop simulation models, decision support, extension, dryland agriculture, and South Africa. Searches were restricted to English language publications.

3.3 Eligibility criteria

Studies were included if they:

i. applied statistical climate analysis, downscaling, or bias correction methods relevant to agricultural applications;
ii. used or evaluated process-based crop simulation models (e.g. APSIM, DSSAT, AquaCrop);
iii. focused on rain fed or dryland systems; and
iv. demonstrated relevance to agricultural advisory services, extension, or decision support.

Studies were excluded if they focused exclusively on irrigated production with no relevance to dryland systems, presented purely theoretical climate modelling without agricultural application, or lacked sufficient methodological transparency.

3.4 Data extraction and classification

From each eligible study, information was systematically extracted on climate data sources; statistical modelling approaches; spatial and temporal scales; crop modelling platforms; calibration and validation procedures; and reported extension or decision support applications. Studies were then categorised according to their dominant analytical emphasis: climate information analysis and simplification, crop model application and evaluation, or integrated climate–crop decision support frameworks.

3.5 Data synthesis and analysis

Evidence was synthesised using a thematic narrative approach suited to heterogeneous modelling studies. First, approaches used to transform complex climate information into extension relevant products, such as probabilistic rainfall metrics, planting window indicators, and drought risk assessments were analysed in relation to usability and interpretability. Second, the performance and limitations of statistical climate models and crop simulation models were assessed with respect to data requirements, representation of climate variability, scalability, and applicability under data limited dryland conditions. Finally, pathways for integrating statistical and crop models within extension decision support systems were synthesised, with emphasis on ensemble modelling, scenario-based analysis, and climate service frameworks designed to support adaptive decision making (Figure 1).

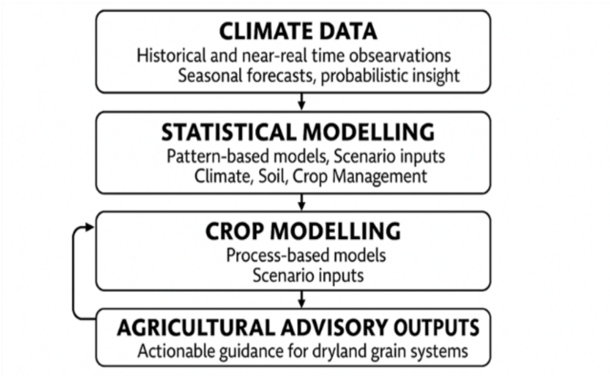

Figure 1. Conceptual framework linking climate data, statistical modelling, crop modelling and agricultural advisory outputs for dryland grain systems in the South African context.

Source: Original author design

3.6 PRISMA ScR flow description

The literature selection process followed the principles of the PRISMA ScR framework. Database searches yielded 40 records, with an additional 5 records identified through grey literature and reference list screening. After removal of duplicate records (15), 30 titles and abstracts were screened for relevance. Of these, 4 records were excluded due to insufficient relevance to dryland systems, modelling approaches, or extension applications. The full texts of 26 articles were assessed for eligibility, resulting in 21 studies included in the final synthesis. Reasons for exclusion at the full text stage included exclusive focus on irrigated systems, lack of methodological transparency, or absence of extension or decision support relevance.

4. Results

4.1 Transparency of models for extension advisory objectives

The synthesis of reviewed studies indicates that model transparency, defined as the degree to which model structure, assumptions and outputs can be clearly understood and explained by extension personnel, is a critical determinant of usability in dryland grain advisory systems. Simple statistical approaches, such as linear and generalized linear models that relate rainfall and temperature indices directly to yield outcomes, were consistently reported as transparent and easier to communicate to farmers than complex simulations (Hansen et al., 2011; Meza et al., 2020). These models enabled extension officers to clearly explain the rationale behind advisories, such as delayed planting in response to rainfall onset risk, thereby strengthening farmer trust and uptake (Table 1). Transparent statistical yield model based, also known as generalised linear models are extension friendly. Example equation for linear regression (formula 1).

$$Yt = \beta_0+\beta_1R_t+\beta_2T_t+\varepsilon_t \qquad (1)$$

where:
Y_t = grain yield in season t (e.g. t ha^{-1})
R_t = seasonal or onset period rainfall index (mm)
T_t = mean growing season temperature (°C)
β_0 = intercept (baseline yield)
β_1, β_2 = estimated effects of rainfall and temperature
ε_t = unexplained variation (error term)

Extension interpretation:

- More rainfall increases yield if $\beta_1 > 0$
- High temperature reduces yield $\beta_2 < 0$

Each coefficient has a direct interpretation for application in agricultural extension. For advisories (e.g. delayed planting) can be explained using the sign and magnitude of coefficients. This simplicity allows extension officers to translate climate information into clear farm level advice, particularly in dryland systems (Figure 2).

However, it is important to note variants that are commonly used in advisory work:

- Generalised Linear Models (e.g. log yield or probability of crop failure)
- Rainfall threshold or onset date models
- Empirical yield–climate indices

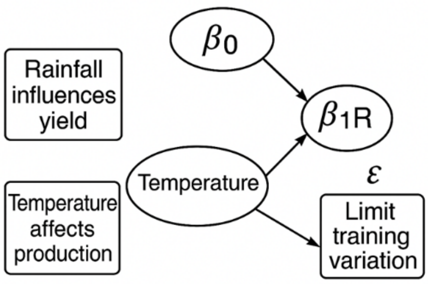

Figure 2. Conceptual representation of a transparent statistical yield model used in dryland grain advisory services.
Source: Original author design

In contrast to Generalized Linear Model, parameterized, process-based crop models, which embed climate inputs within complex internal routines that are not readily interpretable without specialised training. When such models are not supported by adequate visualisation tools and extension capacity building, they are often perceived as “black boxes”, limiting their routine application in extension decision-support contexts. The models are physiological, mechanistic and parameter rich. A simplified representation of a crop growth model (e.g. DSSAT, APSIM, WOFOST) is presented in formula 2.

$$Y=HI\times t=1\sum n[RUE\times PAR_t\times f(T_t,W_t,N_t)] \qquad (2)$$

where:

Y = simulated grain yield
HI = harvest index
RUE = radiation use efficiency
PAR_t = photosynthetically active radiation at time t
T_t = temperature response function
W_t = soil water stress function
N_t = nitrogen stress function
f(·) = nonlinear interaction of stresses over time

Internally, this equation interacts with many sub-models for:

- Soil water balance
- Phenology
- Leaf area development
- Carbon partitioning
- Root growth

In this case, agricultural extension interpretation explains why this model is often opaque. For extension officers and farmers, the implications are:

- Yield emerges from many interacting processes
- Cause effect relationships are not directly visible
- Advisories are difficult to explain without extensive training, graphical visualization and model documentation.

As a result, these models are often perceived as “black boxes” despite their scientific robustness (Figure 3).

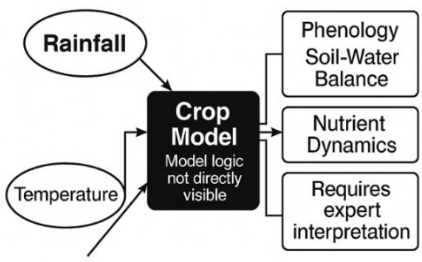

Figure 3. Conceptual representation of a complex process-based crop simulation model used for climate-responsive agricultural decision support. Note: the missing source indication for the bottom arrow suggests unexplained variation (e.g., soil, biota, management, etc.)
Source: Original author design

In the case of complex process-based models, typical applications for agricultural extension include, research and scenario analysis, climate change impact assessment and long-term system optimization. In this context it is necessary to suggest a comparison of models for agricultural advisory purposes (Table 1).

Table 1. Summary comparison of selected models for extension relevance

Model type	Equation form	Interpretability	Extension suitability
Statistical yield model	Single linear / GLM equation	High	Very suitable
Process-based model	Multiple interacting equations	Low–moderate	Limited without support

4.2 Data burden and operational feasibility

Results across case studies show substantial variation in data burden among modelling approaches. Statistical climate–yield models typically required relatively limited inputs—historical rainfall, temperature records and basic management data—and were thus more feasible in data scarce dryland regions (Bhebhe et al., 2021). Process based crop models, by comparison, demanded detailed soil profiles, cultivar parameters and daily weather data, which are rarely available at the spatial resolution required for extension advisory services in South Africa (Walker & Schulze, 2012).

High data requirements were repeatedly identified as a barrier to scaling crop simulation models beyond research environments, particularly within provincial extension systems with limited technical resources.

4.3 Model calibration and relevance for dryland grain systems

Calibration emerged as a decisive factor influencing model performance and relevance for dryland grain advisory objectives. Studies that explicitly calibrated models using local field trial data or long-term station records demonstrated significantly improved yield prediction accuracy and risk characterisation (Lobell et al., 2011; Sultan & Gaetani, 2016). For dryland maize and sorghum systems, calibration of rainfall thresholds, phenological responses to temperature and cultivar specific sensitivity parameters was essential for capturing intra seasonal stress patterns. Uncalibrated models frequently underestimated yield variability and drought risk, reducing their value for extension decision making.

4.4 Summary of selected case studies

Across the reviewed literature, several case studies illustrate contrasting modelling outcomes. In southern Africa, statistical regression models linking seasonal rainfall indices to maize yield variability were successfully used to produce probabilistic planting advisories with demonstrated extension relevance (Archer et al., 2010; Hansen et al., 2011). Conversely, applications of uncalibrated DSSAT and APSIM models at regional scales showed mixed performance, with acceptable mean yield estimates but poor representation of year-to-year variability critical for dryland risk management (Thornton & Herrero, 2014). Hybrid approaches, where climate scenarios were statistically downscaled and then used as inputs to calibrate crop models showed the greatest potential, balancing transparency, agronomic realism and advisory usefulness when appropriately resourced. Overall, the results indicate that modelling approaches most effective for agricultural extension in dryland grain systems are those that optimise transparency, minimise data burden and prioritise local calibration. These characteristics directly enhance the capacity of extension services to deliver credible; climate informed advisories aligned with farmer decision cycles.

4.5 Comparative summary of case studies and advisory relevance

Table 2. summarises representative case studies identified in the reviewed literature, highlighting the modelling approach applied, its primary meaning in an agricultural advisory context, and relevance for dryland grain extension.

Table 2. Comparison of selected case studies on climate and crop modelling for dryland grain agricultural advisory systems.

Case study context	Modelling approach	Meaning in advisory terms	Relevance for dryland grain extension	Reference
Southern Africa maize systems	Statistical rainfall–yield regression	Quantifies probability of yield outcomes based on seasonal rainfall indices	High relevance due to simplicity, transparency and low data requirements	Archer et al. (2010); Hansen et al. (2011)
Semi-arid southern Africa	Climate variability and yield risk analysis	Identifies rainfall distribution effects on inter-annual yield variability	Supports planting window and risk-aware input decisions	Bhebhe et al. (2021)
Regional maize modelling	Process-based DSSAT simulations	Simulates crop growth under alternative climate scenarios	Moderate relevance; high data burden limits routine extension uses	Thornton & Herrero (2014)
South African agro-hydrology	Hydro-climatic and crop response models	Links water availability to crop stress patterns	Useful for drought advisory but requires strong calibration	Walker & Schulze (2012)
Climate-smart agriculture (Africa)	Hybrid statistical–crop modelling	Combines probabilistic climate signals with calibrated crop models	High potential where calibration and capacity are available	Lobell et al. (2011); Sultan & Gaetani (2016)

Source: Author summary of cited references

The comparison illustrates that no single modelling approach is universally optimal. Instead, advisory effectiveness depends on aligning model complexity, data demands and calibration effort with extension capacity and farmer decision needs.

5. Discussion

5.1 Importance of crop modelling in agricultural advisory services

The findings of this review reinforce the central role of crop and climate modelling as enabling tools for modern agricultural advisory services, particularly in dryland production systems exposed to high climatic risk. Crop models provide a formal mechanism for integrating weather variability, soil conditions, cultivar traits and management practices into coherent, decision relevant outputs. Within extension systems, such models support a shift from reactive, experience-based advice towards proactive, risk informed guidance that anticipates seasonal uncertainty rather than responding to shocks after they occur. As demonstrated in the reviewed literature, modelling frameworks that are transparent, well calibrated, and appropriately scaled can meaningfully support decisions on planting dates, cultivar selection, input allocation and drought preparedness. The review also highlights that the value of crop modelling in advisory contexts does not lie solely in yield prediction accuracy, but in the ability to contextualise climate information in agronomic terms that farmers and extension officers can interpret and trust. Statistical climate–yield models are particularly effective in this regard, as they translate complex climate signals into probabilistic outcomes that align with farmer decision cycles. Process based crop models, when locally calibrated, add further value by explaining crop responses to water and temperature stress, thereby supporting longer term adaptation planning. Hybrid approaches that combine these strengths represent a promising pathway for strengthening climate smart extension services in South Africa and similar dryland regions.

5.2 Implications for selected cereal crops

For maize, the dominant dryland cereal in South Africa, future advisory oriented modelling research should prioritise improved representation of intra seasonal rainfall variability, heat stress during flowering and cultivar specific responses to planting date. The reviewed studies indicate that calibrated rainfall–yield models already offer practical value for probabilistic planting advisories, but their integration with crop models can enhance insights into yield variability under extreme seasons (Archer et al., 2010; Lobell et al., 2011). For wheat, particularly under rainfed conditions in marginal areas, modelling efforts need to focus on temperature thresholds, early season establishment risk and terminal drought. Although wheat systems are generally better monitored than other grains, extension relevant models must be simplified and tailored to support smallholder and emerging farmers who lack access to detailed field data (Walker & Schulze, 2012).

For sorghum, which is inherently more drought tolerant, future research should emphasise modelling of resilience traits rather than maximum yield alone. Crop models calibrated for sorghum can support advisory services by identifying environments where sorghum offers a lower risk alternative to maize under projected climate variability, thereby contributing to diversification-based adaptation strategies (Sultan & Gaetani, 2016).

5.3 Implications for legume crops

Legumes are increasingly important for both food security and soil fertility in dryland systems yet remain underrepresented in extension-oriented modelling studies. For soybeans, future research should integrate temperature sensitivity during reproductive stages with rainfall variability models, as yield losses are often associated with short heat and moisture stress periods. Statistical models linked to phenology-based crop simulations can improve advisory timing for planting and cultivar choice (Meza et al., 2020). For dry beans and groundnuts, modelling priorities include soil moisture availability, planting window sensitivity and the interaction between water stress and disease risk. The review suggests that relatively simple, calibrated models may offer substantial advisory value for these crops due to their shorter growing seasons and sensitivity to early season conditions. Embedding such models within extension services could enhance crop diversification and risk spreading among smallholder farmers.

5.4 Future research directions and extension integration

Across all grain types reviewed, future research should focus on strengthening the interface between modelling and extension practice rather than model complexity alone. Priority areas include routine calibration using local trial and farmer field data, co production of advisory outputs with extension officers, and development of communication tools that clearly express uncertainty. Investment in extension capacity to interpret and contextualise modelling outputs is equally critical, as even the most robust models have limited impact if poorly understood or mistrusted. The findings of the study underscores that crop modelling is not an end, but a decision support instrument whose effectiveness depends on transparency, calibration and institutional integration. Aligning modelling research with the practical realities of agricultural advisory services will be essential for advancing climate smart agriculture in South Africa's dryland grain systems.

5. Conclusions

This review synthesised literature published between 2010 and 2026 to evaluate how statistical climate modelling and crop simulation approaches can be effectively integrated into agricultural extension advisory services, with a particular focus on dryland grain production systems. The major finding is that modelling approaches offer substantial value to extension practice when they are transparent, calibrated to local conditions and aligned with farmer decision cycles. Simple statistical models were consistently shown to be effective in translating complex climate information into probabilistic advisories, while process based crop models added agronomic depth when supported by adequate data and local calibration. Hybrid modelling frameworks that combine these strengths emerged as the most promising pathway for climate informed advisory services. From a South African agricultural extension perspective, the review highlights that the primary challenge is not the absence of models, but rather their operationalisation within extension systems constrained by limited data, technical capacity, and high farmer to extension officer ratios. Extension relevant modelling must therefore prioritise usability, interpretability, and scalability. Embedding calibrated climate and crop models into routine extension workflows, such as seasonal planning meetings, planting advisories and drought early warning systems can strengthen evidence-based decision making and improve farmer resilience, particularly in dryland maize, sorghum and legume systems. The findings also have broader global relevance. Dryland grain production systems worldwide face similar challenges associated with increasing climate variability, non-stationarity, and uncertainty. The emphasis on transparency, low data burden and uncertainty communication is therefore applicable beyond South Africa, particularly in other semi-arid regions of sub-Saharan Africa, Asia, and Latin America. Strengthening the interface between climate science and extension through appropriately scaled modelling contributes directly to global climate smart agriculture objectives and resilience building under climate change. Despite its contributions, this review has several limitations. It relied on published literature and secondary data, which may underrepresent emerging extension innovations not yet documented in peer reviewed sources. In addition, heterogeneity in study designs and evaluation metrics limited direct quantitative comparison across models. The review also focused primarily on biophysical modelling approaches, with less emphasis on socio economic and institutional factors that influence advisory uptake. Future research should therefore prioritise longitudinal evaluations of modelling-based advisories within extension programmes, integration of socio-economic variables into climate–yield models, and development of participatory calibration approaches involving farmers and extension officers. Specific attention should be given to under researched crops such as dry beans and groundnuts, as well as to gender and resource sensitive advisory design. Advancing these research directions will be essential for ensuring that climate and crop modelling contributes meaningfully to resilient, inclusive, and sustainable agricultural extension systems.

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