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Evaluating Scenario Based Performance of DSSAT Response to Soil Depth, Initial Soil Water Content and Choice of *Zea mays* L. Cultivar Selection in Semi-Arid North West Province in South Africa

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ABSTRACT

Process-based crop models are widely used to assess crop responses to climate variability, yet their performance is highly sensitive to assumptions regarding soil properties, initial soil water content and cultivar selection, particularly in spatially heterogeneous, rainfed systems. This study evaluates the performance of the DSSAT-CERES-Maize model across the North West Province of South Africa using a fine-scale, quinary catchment-based framework. Four scenario simulations were developed to examine the influence of soil depth, pre-season soil moisture and cultivar choice on simulated maize yields. Model outputs were evaluated against district-level reported yields for the 1981–1999 period using a comprehensive multi-criteria assessment framework incorporating distributional tests, correlation analysis, weighted regression and multiple performance metrics. Results indicate that DSSAT effectively reproduces inter-annual yield variability across spatial scales, with stronger agreement at the district level than at the provincial scale. Scenario performance was highly sensitive to soil depth and initial soil water assumptions, with the scenario incorporating deeper effective rooting depth and intermediate pre-season soil moisture consistently achieving superior agreement across most evaluation criteria. Cultivar selection influenced yield variability, highlighting the importance of representative genetic parameterisation in regional applications. While simulated and reported yield medians did not differ significantly at the district scale, error magnitudes and efficiency metrics varied spatially, reflecting the dominant influence of climate variability under rainfed conditions. These findings demonstrate that spatially explicit, scenario-based evaluation enhances confidence in crop model applications and provides valuable insights for agrometeorological assessments, climate adaptation planning and decision support in semi-arid, water-limited agricultural systems.

1 | Introduction

Process-based crop simulation models are valuable tools for assessing the impacts of climate variability, climate change and management practices on crop yields (Zinyengere et al. 2015). These models enable rapid and cost-effective exploration of physical systems beyond what is feasible through traditional field experimentation alone (Choruma et al. 2019). They have been widely applied at regional to global scales (Liu et al. 2007; Liu 2009; Fader et al. 2010) to evaluate agricultural systems under changing climatic conditions (Choruma et al. 2019). However, for model outputs to be meaningful, calibration and validation are required under the specific environmental and management conditions for which the models are intended to be used (Folberth et al. 2012). Such validation has largely been conducted in high-input, well-managed agricultural systems (Folberth et al. 2012; Zinyengere et al. 2015). While Sub-Saharan Africa (SSA), which is a region characterised by low yields and high vulnerability to climate change impacts, such as an increase in maximum temperature (Landman et al. 2018), remains largely underrepresented (Liu et al. 2007, 2008; Zinyengere et al. 2015).

Early crop modelling applications in SSA often reported substantial discrepancies between simulated and observed yields, reflecting limitations in climate, soil and land-use input data as well as short validation periods (Jones and Thornton 2003; Thornton et al. 2009). Although more recent studies have demonstrated improved performance using higher-quality datasets and local calibration, data constraints such as the availability of spatially resolved soil and management information continue to limit robust model evaluation across the region (Zinyengere et al. 2015; Ajilogba and Walker 2023). In addition, many crop modelling studies rely on coarse spatial resolutions that implicitly assume environmental homogeneity, an assumption that can introduce substantial errors in yield simulations in heterogeneous landscapes and microclimates (Gardner et al. 2021; Kephe et al. 2021). Together, these challenges highlight the need for crop model evaluation frameworks that explicitly account for spatial heterogeneity in data-limited regions.

The Quinary Catchment Database (QCD) provides a valuable framework for fine-scale modelling in southern Africa. Covering South Africa, Lesotho and Eswatini, the QCD integrates long-term daily climate data with spatially explicit environmental information at a finer resolution than typically used in regional crop modelling studies (Schulze et al. 2011). Its application enables improved representation of spatial variability in weather and environmental conditions that are often masked at broader scales.

The Decision Support System for Agrotechnology Transfer (DSSAT) CERES-Maize model has been widely applied and evaluated across a range of climatic and management conditions. In southern Africa, DSSAT has been shown to reproduce maize yield variability under rainfed conditions at sub-national scales (Walker and Schulze 2008; Zinyengere et al. 2015). Its robustness has also been demonstrated through multi-model intercomparison studies, including the Agricultural Model Intercomparison and Improvement Project (AgMIP), where DSSAT-CERES-Maize has been identified as one of the most widely used and comprehensive maize simulation models due to its representation of soil–plant–atmosphere processes (Lizaso et al. 2011; Rosenzweig et al. 2013; Bassu et al. 2014; Chitsiko et al. 2022).

Model performance in DSSAT is known to be sensitive to assumptions related to soil depth, initial soil water content and cultivar-specific genetic coefficients, as these parameters directly regulate root development, water stress, phenology and biomass accumulation (Menefee et al. 2021; Gavasso-Rita et al. 2024). In heterogeneous environments, misrepresentation of these factors can lead to systematic over- or underestimation of yield responses, particularly under rainfed conditions where water availability is a dominant constraint. Conducting scenario-based simulations to these assumptions is therefore critical for improving confidence in model-based assessments.

Maize (*Zea mays* L.) is South Africa's most important staple crop and a key component of food security in the Southern African Development Community. The Free State and North West provinces together account for approximately 60% of national maize production, predominantly under rainfed commercial farming systems (Grant et al. 2012; Adisa et al. 2018). Spatial variability in climate, soils and land use across these regions underscores the importance of locally relevant modelling approaches to support yield prediction and climate adaptation planning.

This study applies the DSSAT-CERES-Maize model at a finer spatial resolution using quinary catchment-level data to evaluate its ability to reproduce reported maize yields in the North West Province of South Africa. Model performance is assessed at both provincial and district levels, and scenario-based analyses are conducted to examine simulated yields to assumptions regarding effective rooting depth, initial soil water content and cultivar selection. By combining multi-scale validation with targeted scenario-based analyses, the study aims to identify key sources of uncertainty in yield simulations and to inform robust crop modelling strategies for water-limited, rainfed agricultural systems.

2 | Materials and Methods

2.1 | Study Site

The study focused on the North West Province (NWP) of South Africa (Figure 1) which spans approximately 116,320 km^2 (Botai et al. 2016). In the 2018/2019 season, it accounted for about 18.6% of the land used for maize production in South Africa (Diko and Jun 2020). The dry western regions of the maize belt, comprising the North West and Free State provinces, produce over 60% of South Africa's maize, while the wetter eastern regions, Mpumalanga (approximately 24%) and KwaZulu-Natal (< 5%), contribute the remainder (Adisa et al. 2018). With an estimated 43.9% of its land categorised as arable, the NWP plays a critical role in the country's food production (Adisa et al. 2019).

The districts which report on maize yield to the Department of Agriculture, Land Reform and Rural Development are Bloemhof, Brits, Christiana, Coligny, Delareyville, Klerksdorp, Koster, Lichtenburg, Marico, Potchefstroom, Rustenburg, Schweizer–Reneke, Swartruggens, Ventersdorp, Vryburg and Wolmaransstad.

2.2 | Reported Maize Yield Data

District-level market maize yield data was obtained from the Department of Agriculture, Land Reform and Rural

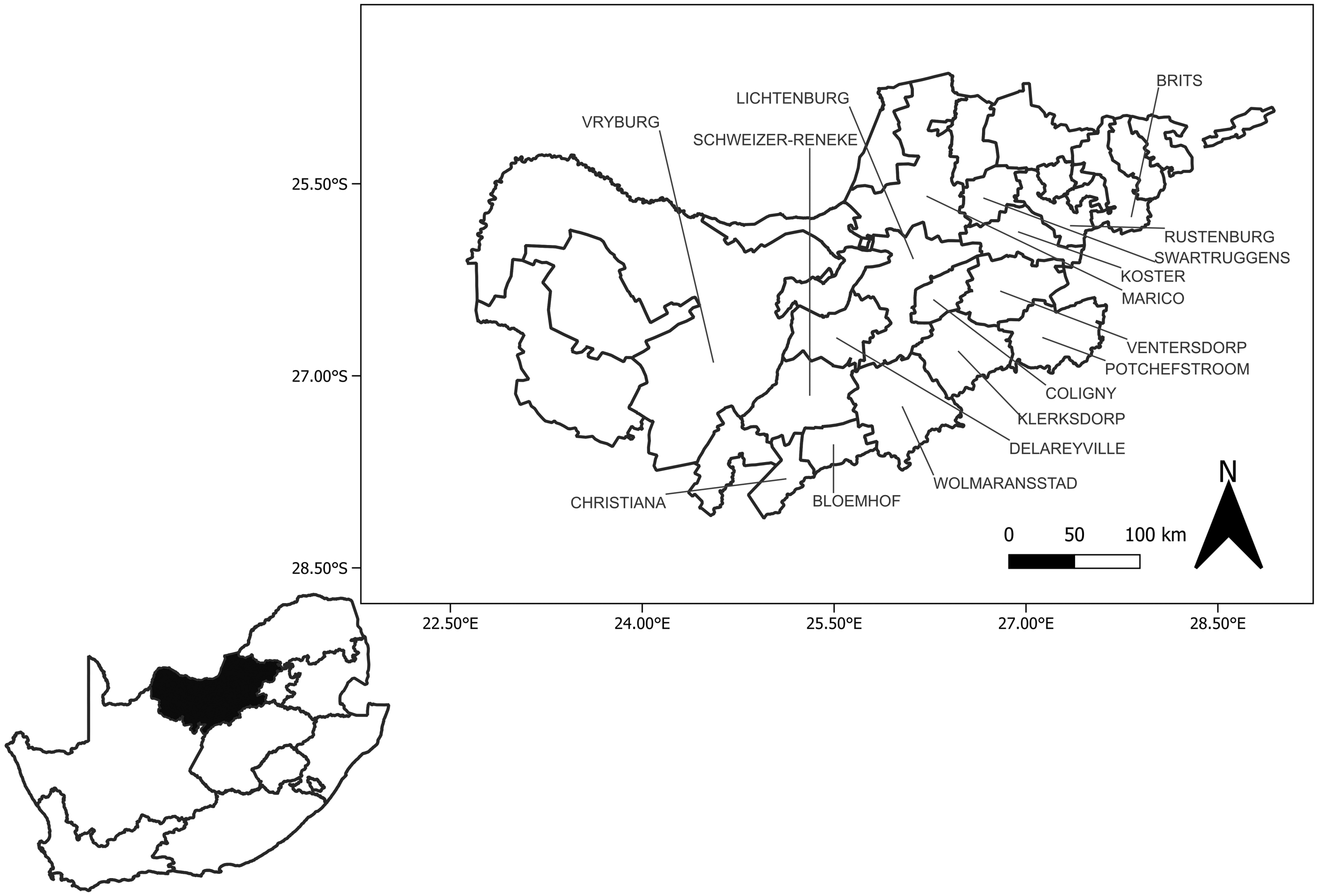

FIGURE 1 | North West Province location within South Africa and magisterial districts within the Province which report maize yield.

Development (DALRRD) for the NWP. The yield estimates are generated by means of Geographic Information System (GIS) technologies along with robust statistical methods conducted by the Crop Estimate Committee (CEC) (Mangani et al. 2025). To improve the accuracy of the estimates aerial surveys are conducted over provinces heavily involved with key crops such as maize. Yield data for the above-mentioned districts were available from 1981 to 2022, apart from Swartruggens, which had no maize yield data after 2004. The reported yields varied across districts, highlighting the potential differences in agricultural practices, environmental conditions or reporting mechanisms between districts.

2.3 | The DSSAT Model

The DSSAT cropping system model software (DSSAT v4.8, Hoogenboom et al. 2021) uses a modular approach, as described by Porter et al. (2000) and Jones et al. (2001). It simulates crop growth, development and yield over time on a uniform area of land, incorporating selected management practices and the influence of environmental factors (Jones et al. 2003). Key environmental inputs include daily solar radiation, minimum and maximum temperatures, precipitation and soil properties such as texture and depth. The CERES-Maize module within DSSAT has been extensively calibrated for southern Africa (du Toit et al. 1994, 1997) and offers a wide range of management options that can be simulated (Walker and Schulze 2006).

2.4 | The South African QCD

For operational decision-making in water resources management, South Africa has been subdivided into hydrological catchment areas of varying resolution ranging from primary catchments (large catchments representing the first level of subdivision) to quaternary catchments (small catchments representing the fourth level of subdivision). Schulze et al. (2011) further subdivided the quaternary catchments into a fifth level of subdivision known as quinary catchments, where this delineation was based on altitude criteria. Each quaternary catchment was subdivided into three quinary catchments: the upper, middle and lower, of unequal areas but similar topography and altitude (Schulze et al. 2011). These quinary catchments serve as hydrological and agricultural response zones.

Schulze et al. (2011) developed a database of input data to support biophysical modelling (of a hydrological and agricultural nature) in the quinary catchments, known as the QCD. Here a set of input data relating to inter alia daily weather data and soil properties was derived for each quinary catchment in the country. In this study, data were sourced from this database to facilitate the development of inputs to the DSSAT model for quinary catchments located in the NWP.

In the NWP, there are 258 quinary catchments, of which 196 were identified as being long-standing maize producing areas. This identification was carried out using a shapefile titled

Agricultural Regions Based on Predominant Type of Farming Activity (Institute for Cartographic Analysis, 1978). A quinary catchment was considered suitable for modelling if its centroid overlapped with areas mapped for grain activity.

2.5 | Observed Environmental and Meteorological Input Data

The environmental data required for the DSSAT model were obtained from the QCD (Schulze et al. 2011). The weather data in this database spans from 1950 to 1999 and includes daily values for solar radiation, maximum temperature, minimum temperature, precipitation and relative humidity for each quinary catchment. The temperature and precipitation data were derived from station records, while solar radiation and relative humidity were derived from temperature data and other inputs such as latitude (Schulze et al. 2011).

Soil profile data in the QCD include information on soil texture, depth and soil water retention characteristics for each quinary catchment. These data were derived from Land Type information (SIRI (Soil and Irrigation Research Institute) 1987) using the methodology described by Schulze (2007), which aggregates soil properties to the quinary catchment scale. The spatial resolution of the soil dataset therefore corresponds to the quinary catchment level, with each catchment represented by a single, spatially averaged soil profile. The soil data are provided in tabular format and were parameterised to generate DSSAT-compatible soil input files, including layer-wise estimates of soil water limits and hydraulic properties.

2.6 | Cultivar Input Data

The DSSAT model requires crop genetic data, which influences various stages of crop development and growth. For this study, two maize varieties which were considered representative for the time and region of southern Africa were selected. Selecting for representative cultivars has been done in previous process-based modelling studies to capture the range of cultivar responses rather than to replicate cultivar use at individual farm level (Bassu et al. 2014; Gummadi et al. 2020). The first cultivar, known as the PAN6479 hybrid variety, was described and calibrated by Cammarano et al. (2020). This hybrid was commonly grown from 1980 to 2010 in the region of southern Africa (Cammarano et al. 2020). The second variety is an open-pollinated cultivar called ZM521, which was released in eastern and southern Africa between 2000 and 2005 (Tesfaye et al. 2014).

Both varieties are classified as intermediate maturity types, meaning they reach physiological maturity within a moderate timeframe. Maturity levels in maize are typically determined by the number of growing degree days (GDD) required from planting to maturity, with intermediate types falling between early-maturing varieties (which require fewer GDD and are suited for shorter growing seasons) and late-maturing varieties (which require more GDD and are often planted in regions with longer growing seasons) (Nape 2011; Tesfaye et al. 2014). However, their calibrated genetic coefficients (Table 1) result in varying model outputs due to differences in growth and development. For example, cultivar ZM521 (220) has a longer juvenile phase (P1) than PAN6479 (200) by 20 GDD, allowing for prolonged vegetative growth. Additionally, ZM521 has a higher potential kernel number per plant (920) compared to PAN6479 (500), which may contribute to higher yield under favourable conditions, provided adequate resources are available for grain filling.

TABLE 1 | Calibrated cultivar genetic coefficients of the PAN6479 and ZM521 maize varieties from Cammarano et al. (2020) and Tesfaye et al. (2014), respectively.

Variant	P1	P2	P5	G2	G3	PHINT
PAN6479	200	0.6	710	500	8.5	38.9
ZM521	220	0.1	640	920	7.1	38.9

Note: P1 = Thermal time from seedling emergence to the end of the juvenile phase (expressed in degree days above a base temperature of 8°C) during which the plant is not responsive to changes in photoperiod. A photoperiod refers to the duration of light a plant is exposed to in a 24-h cycle.
P2 = Extent to which development (expressed as days) is delayed for each hour increase in photoperiod above the longest photoperiod at which development proceeds at a maximum rate (which is considered to be 12.5 h).
P5 = Thermal time from silking to physiological maturity (expressed in degree days above a base temperature of 8°C).
G2 = Maximum possible number of kernels per plant.
G3 = Kernel filling rate during the linear grain filling stage and under optimum conditions (mg/day).
PHINT = Phylochron interval; the interval in thermal time (degree days) between successive leaf tip appearances.

2.7 | Crop Management Information

Planting dates for each quinary catchment were determined using seasonal rainfall criteria following Schulze and Maharaj (2004), while planting density and row spacing were specified using rainfall-based relationships developed by Estes et al. (2013). Crop management was implemented using a uniform DSSAT management file to ensure consistency across simulations. Soil nutrient dynamics were not explicitly simulated because soil chemical properties were not available in the QCD. Consequently, simulations assumed non-limiting nutrient conditions, representing well-managed commercial maize production systems typical of large-scale rainfed farming in the NWP. This approach was adopted to isolate the effects of climate variability, soil water availability and cultivar selection on simulated yields, rather than to reproduce nutrient-limited conditions. To avoid cumulative legacy effects, such as differences in how land is managed across the study area outside of the maize growing season, simulations were re-initialised annually, with soil water conditions reset before planting and soil nitrogen pools maintained at non-limiting levels. No irrigation was applied, as irrigated areas are spatially restricted within the province and were excluded from the analysis.

2.8 | Scenario Simulations

The DSSAT-CERES-Maize model was applied using four scenario simulations (Table 2), varying in cultivar selection and soil physical characteristics, specifically soil depth and initial soil water content. Scenario-based variation of soil and cultivar

TABLE 2 | Simulation scenario input parameters.

Simulation scenario	Cultivar	Maximum soil depth	Initial soil water content
SS1	PAN6479	QCD Value	SLLL
SS2	PAN6479	120 cm	50% of PAW (Avg. of SLL and SDUL)
SS3	ZM521	QCD Value	SLLL
SS4	ZM521	120 cm	50% of PAW (Avg. of SLL and SDUL)

parameters is a widely adopted approach in process-based crop modelling to explore scenario-based uncertainty in simulated yields (Jones et al. 2003; Bassu et al. 2014; Gavasso-Rita et al. 2024). Soil depth was varied across scenarios because the average soil depth reported for each quinary catchment in the QCD represents a catchment-scale mean and may underestimate the depth of soils preferentially cultivated for arable crop production (Schulze et al. 2011; Kephe et al. 2021). Across the NWP, average quinary catchment soil depths in the QCD range from 15 to 118 cm. For baseline Scenario Simulations SS1 and SS3, soil depth values were adopted directly from the QCD. For SS2 and SS4, soil depth was adjusted to 120 cm, representing a conservative upper bound for effective maize rooting depth and consistent with soil profile depths commonly used in DSSAT and other crop modelling studies in southern Africa (Hsiao et al. 2009; Zinyengere et al. 2011; Biazin and Stroosnijder 2012; Steduto et al. 2009; Dahri et al. 2024).

To clarify the treatment of soil depth in the adjusted scenarios (SS2 and SS4), soil profiles were conceptually extended to a maximum depth of 120 cm to represent increased effective rooting depth, rather than by introducing new or synthetic soil horizons. Soil physical characteristics, including soil texture, bulk density and soil water retention parameters (SLLL, SDUL and SAT), were not modified from the original QCD values. Where soil depth was increased, the physical properties of the deepest existing soil layer were propagated downward to the extended depth, consistent with standard practice in DSSAT when evaluating the influence of rooting depth on crop water availability. This approach isolates the effect of effective soil depth from changes in soil physical properties, allowing a clearer interpretation of scenario-driven yield responses.

Initial soil water content was specified to represent contrasting but plausible pre-season soil moisture conditions within each quinary catchment. For the baseline scenarios (SS1 and SS3), soil water content at the start of the simulation period (15 August, corresponding to the end of the dry winter season prior to planting) was set to the lower limit of plant-extractable soil water (SLLL), representing a dry pre-season condition consistent with DSSAT conventions and typical end-of-winter soil moisture depletion in semi-arid rainfed systems (Jones et al. 2003).

For the adjusted scenarios (SS2 and SS4), initial soil water content was set to 50% of plant-available water (PAW), defined as the midpoint between the lower limit (SLLL) and drained upper limit (SDUL). This represents a more favourable but realistic pre-season soil moisture condition, reflecting areas within each quinary catchment where maize is preferentially cultivated on deeper, higher water-holding soils. Because quinary catchments are spatially heterogeneous and not uniformly farmed, this assumption provides a more representative approximation of conditions on productive agricultural land. In the absence of site-specific initial soil moisture measurements, crop simulation studies commonly initialise soils using intermediate PAW fractions to represent unsaturated but non-limiting water availability and to evaluate scenario-based sensitivity to starting conditions (Saseendran et al. 2013; Zinyengere et al. 2015; Menefee et al. 2021).

All simulations were initiated prior to planting to allow soil water conditions to equilibrate under prevailing climatic conditions before crop establishment, following recommended DSSAT practice for long-term simulations (Jones et al. 2003). Model simulations spanned a 20-year period from 1980 to 1999. The winter period between successive maize crops was not simulated because land use and management during this season (e.g., fallow or alternative cropping) vary widely across farms and are poorly documented at regional scales, potentially introducing additional uncertainty (Zinyengere et al. 2015). To account for this in the modelling, soil water conditions at the start of each simulated season were re-initialised according to the scenario-specific values presented in Table 2, consistent with standard practice in scenario-based crop modelling studies (Folberth et al. 2012; Bassu et al. 2014).

Simulated maize yields were aggregated from quinary catchment scale to district level based on the spatial location of each catchment within district boundaries, enabling comparison with available administrative-level yield statistics (Thornton et al. 2009; Folberth et al. 2012). As quinary catchments are hydrological units and do not necessarily align with administrative boundaries, some catchments intersected more than one district. In such cases, the quinary catchment was included in each intersecting district, such that some quinary catchments contributed to multiple districts. Although simulations were conducted for the full 1950–1999 period, analyses focused on the 1981–1999 interval to align with the availability of district-level reported maize yield data from the Department of Agriculture, Land Reform and Rural Development (DALRRD).

2.9 | Statistical Analysis

The significance of trends of reported maize yield data at the provincial and district level was assessed using a Mann–Kendall (MK) trend test in Rstudio. The MK test can detect upward trends which may be due to advancements in seeds, fertilisers, pesticides or crop management, or downward trends which may be due to adverse environmental conditions. Analysing for trends is essential to understand whether a yield dataset would need to be subjected to a detrending procedure to make the datasets comparable.

The distributions of simulated and reported yields across the NWP were analysed using the Kolmogorov–Smirnov (K–S) test in RStudio to assess differences in their shapes and overall statistical distributions. This test evaluates whether the two datasets originate from similar underlying distributions, thereby assessing not only differences in central tendency but also differences in spread, skewness and distributional shape. Variances of yields in the four scenarios were compared with reported yields using the F-test to determine whether there were significant differences in variability. Statistical tests were conducted at a 95% significance level ($\alpha = 0.05$).

2.10 | Correlation Analysis

To assess the model's ability to emulate patterns in the reported yield data, a Spearman's rank correlation analysis between simulated yields and reported yields was done as the data were not normally distributed. A correlation analysis is a statistical method employed to assess the strength and direction of relationships between variables. A correlation coefficient above 0.52 was calculated to be significant at 95% confidence through 19 years of comparison.

Correlation-based evaluation of DSSAT performance is widely applied in crop modelling studies, with the strength of association typically interpreted qualitatively (e.g., weak, moderate, strong) rather than through rigid thresholds (Walker and Schulze 2008; Zinyengere et al. 2015; Ajilogba and Walker 2023). The thresholds adopted in this study have been defined as:

$r \leq 0.3$	Non or very weak relationship
$0.3 < r \leq 0.5$	Weak relationship
$0.5 < r \leq 0.7$	Moderate relationship
$0.7 < r \leq 0.8$	Strong relationship
$r > 0.8$	Very strong relationship

2.11 | Model Performance

The four crop simulation scenarios were compared with reported data over a 19-year period (1981–1999). Eight model performance metrics were used to assess crop yield simulations across four scenarios (Table 3). Accuracy, as defined in the PerMat package in RStudio (Das 2024), provided a measure of relative predictive performance across scenarios. Additionally, RMSE, nRMSE, CVRMSE and MAE quantified different aspects of absolute and relative prediction error, allowing comparison across datasets with differing scales. NSE, PBIAS and the index of agreement (d) evaluated model skill, systematic bias and overall agreement with observed yield variability. Together, these metrics offered a comprehensive evaluation of both the magnitude and direction of errors, model fit and predictive reliability. Formulas for the evaluation metrics can be found in Table S1.

The adjusted R^2 is a modified version of the standard R^2 that accounts for the number of predictors in the model. In WLS regression, observations are given weights based on their reliability or

TABLE 3 | Model performance criteria with reasoning and acceptable values for the study.

Metric	Units	Purpose	Interpretation	Accepted thresholds	Supporting references
Accuracy	Unitless (0–1)	Relative predictive performance	Values closer to 1 indicate better fit	≥ 0.70 = acceptable	Rashid et al. (2021) and Das (2024)
RMSE	kg/ha	Absolute prediction error	Lower values indicate better fit	No fixed threshold	Choruma et al. (2019) and Rashid et al. (2021)
nRMSE	Unitless	Scale-independent RMSE	0 = perfect; lower is better	< 0.30 = acceptable	Das (2024)
CVRMSE	Unitless	Error relative to mean observed yield	Lower values indicate better fit	< 0.30 = acceptable	Das (2024) and Yersaw et al. (2024)
MAE	kg/ha	Average absolute deviation	Lower values indicate better fit	No fixed threshold	Das (2024)
NSE	Unitless (−∞ to 1)	Predictive skill relative to mean	1 = perfect; 0 = equal to mean; < 0 worse than mean	≥ 0.40 = acceptable	Choruma et al. (2019)
PBIAS	%	Systematic over-/under-estimation	0 = unbiased; sign indicates direction	$\lvert PBIAS \rvert \leq 25\%$ (acceptable)	Choruma et al. (2019)
Index of agreement (d)	Unitless (0–1)	Overall agreement	1 = perfect; 0 = no agreement	≥ 0.75 = acceptable	Liu et al. (2017)

TABLE 4 | Mean, median, standard deviation, interquartile range, 10th and 90th percentiles of the reported yield and of four Scenario Simulations across the North West Province from 1981 to 1999.

Yield data	Mean yield (kg/ha)	Median yield (kg/ha)	Standard deviation (kg/ha)	Interquartile range	10th percentile	90th percentile
Reported yield	1707	1600	903	1320	452	2972
SS1	1396	1262	898	1230	270	2648
SS2	1664	1552	990	1373	402	3091
SS3	1703	1464	1181	1600	294	3305
SS4	2019	1798	1279	1784	435	3825

variance, and the adjusted R^2 is computed using this weighted model. In weighted regressions, it helps in handling heteroscedasticity or unequal variances.

$$\text{Adjusted } R^2 = 1 - \frac{(1 - R^2)(N - 1)}{N - p - 1}$$

where R^2 is the sample R-square, p is the number of predictors and N is the total sample size. A higher adjusted R^2 value indicates less error variance and therefore a better performing model. A value of equal to or above 0.6 is considered as an acceptable model as it accounts for 60% of the observed variation (Choruma et al. 2019).

3 | Results

3.1 | Provincial Level

To compare a scenario to the reported yields at the provincial level a range of descriptive statistics were calculated. The descriptive statistics of mean, median, standard deviation, interquartile range (IQR), 10th and 90th percentiles for the reported data and the four scenarios across the NWP for the 19 years (1981–1999) are presented in Table 4. SS1 displayed the lowest IQR, while SS4 displayed the highest IQR, indicating that SS1 has the least variability in maize yield, while SS4 has the greatest variability of maize yield across the NWP. The scenarios which used cultivar ZM521, SS3 and SS4, displayed higher variability, indicating that this variety may be more sensitive to environmental fluctuations.

The maize yield datasets (reported and scenarios) for each 19-year period across the NWP did not show any significant trends from the MK test ($p > 0.05$). The Kolmogorov–Smirnov test revealed that the distribution of SS2 yields did not differ significantly from the reported data ($p > 0.05$), whereas the distributions of SS1, SS3 and SS4 differed significantly from reported yields ($p < 0.05$).

The time-series comparison of reported and simulated maize yields averaged by harvest year across the NWP (Figure 2a) shows that all DSSAT simulation scenarios reproduced the timing of major inter-annual yield fluctuations, including years of low and high production. To quantify this agreement, a Spearman's rank correlation analysis was performed between simulated and reported yields, yielding strong positive correlations across all scenarios, with correlation coefficients ranging from 0.74 to 0.79 (Figure 2b). SS2 achieved the highest correlation ($r = 0.79$), while SS3 showed the lowest ($r = 0.74$). Although SS4 generally overestimated maize yields (PBIAS≈18.3%), it still produced a high correlation coefficient ($r = 0.76$), indicating that inter-annual yield variability was well captured despite bias in magnitude.

Given the presence of heteroscedasticity among the datasets, weighted least squares (WLS) regression was applied to assess the extent to which simulated yields explained variability in reported maize yields across the NWP. Among the scenarios, SS2 and SS4 exhibited the highest explanatory power, with adjusted coefficients of determination exceeding 0.6 (Figure 2c,e). SS2 achieved the highest adjusted coefficient of determination (0.66), indicating that 66% of the variance in reported yields was explained by simulated yields (Figure 2c). SS4 also exceeded this threshold, although with slightly lower explanatory power (Figure 2e). In contrast, SS1 and SS3 showed lower adjusted coefficients of determination values, despite comparable correlation strengths.

Model performance varied across the four scenario simulations when evaluated against reported maize yields at the provincial scale for the 1981–1999 period (Table 5). Among the scenarios, SS2 consistently demonstrated superior performance across most evaluation metrics. SS2 achieved the second highest accuracy score (0.97), indicating strong agreement between simulated and reported yields. This was accompanied by the lowest error metrics, including RMSE (617.19 kg/ha), nRMSE (0.16), CVRMSE (0.36) and MAE (0.32), reflecting reduced absolute and relative simulation error compared to the other scenarios. SS2 also recorded minimal bias (PBIAS = −2.50%) and the highest index of agreement ($d = 0.89$). The adjusted coefficient of determination (adjusted $R^2 = 0.66$) indicates that approximately two-thirds of the variance in reported yields was explained by the simulation.

In terms of predictive skill, SS2 was the only scenario to exceed the Nash–Sutcliffe efficiency (NSE) acceptability threshold of 0.40, achieving an NSE value of 0.53. This indicates improved predictive performance relative to a mean-based benchmark. In contrast, SS1, SS3 and SS4 recorded NSE values below the threshold (0.38, 0.21 and 0.02, respectively), indicating reduced predictive skill.

SS1 and SS3 exhibited relatively high accuracy values (0.86 and 0.98, respectively) and low bias; however, both scenarios were associated with higher error metrics and lower NSE values compared to SS2. SS4 recorded the highest error values across RMSE, nRMSE, CVRMSE and MAE, despite achieving a moderate adjusted R^2 value of 0.60, indicating that variance explanation did not translate into improved predictive performance.

Evaluation against predefined acceptable performance criteria (Table 6) further highlighted differences among scenarios. SS2 satisfied the highest proportion of criteria (85.71%), followed by SS4 (71.43%), while SS1 and SS3 each satisfied 57.14% of the criteria. Overall, SS2 demonstrated the most consistent performance across accuracy, error, bias, variance explanation and predictive skill metrics.

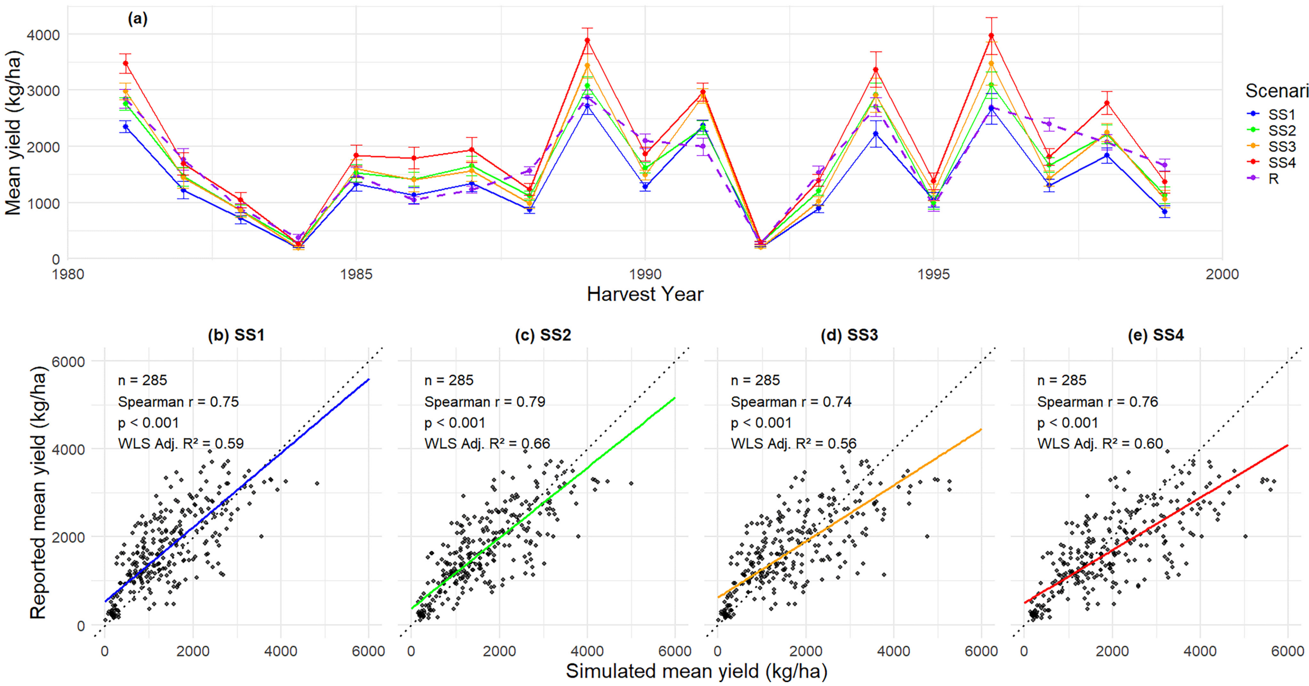

FIGURE 2 | (a) Time series of annual, spatially averaged maize yields across the North West Province from 1981 to 1999, shown for four scenario simulations (SS1–SS4) and reported data. Error bars represent the standard error of district-level yields within the province for each harvest year. The dashed line denotes reported yields, while solid-coloured lines represent the scenario simulations. (b–e) Scatterplots of annual district-level simulated versus reported maize yields across the North West Province for SS1–SS4, respectively. The dashed line indicates the 1:1 relationship, and the solid-coloured lines represent WLS regression fits.

TABLE 5 | Model evaluation criteria for the four scenario simulations when compared with reported yields across the North West Province for the period 1981 to 1999.

	Accuracy	RMSE	nRMSE	CVRMSE	MAE	NSE	PBIAS	*d*	Adjusted R^2
SS1	0.86	710.77	0.19	0.41	0.37	0.38	−18.20	0.84	0.59
SS2	0.97	617.19	0.16	0.36	0.32	0.53	−2.50	0.89	0.66
SS3	0.98	799.95	0.21	0.47	0.41	0.21	−0.21	0.84	0.56
SS4	0.76	894.56	0.23	0.52	0.44	0.02	18.27	0.82	0.60

TABLE 6 | Acceptable model evaluation criteria met.

	Accuracy	nRMSE	CVRMSE	NSE	PBIAS	*d*	Adjusted R^2	% Satisfactory
SS1	✓	✓	×	×	✓	✓	×	57.14%
SS2	✓	✓	×	✓	✓	✓	✓	85.71%
SS3	✓	✓	×	×	✓	✓	×	57.14%
SS4	✓	✓	×	×	✓	✓	✓	71.43%

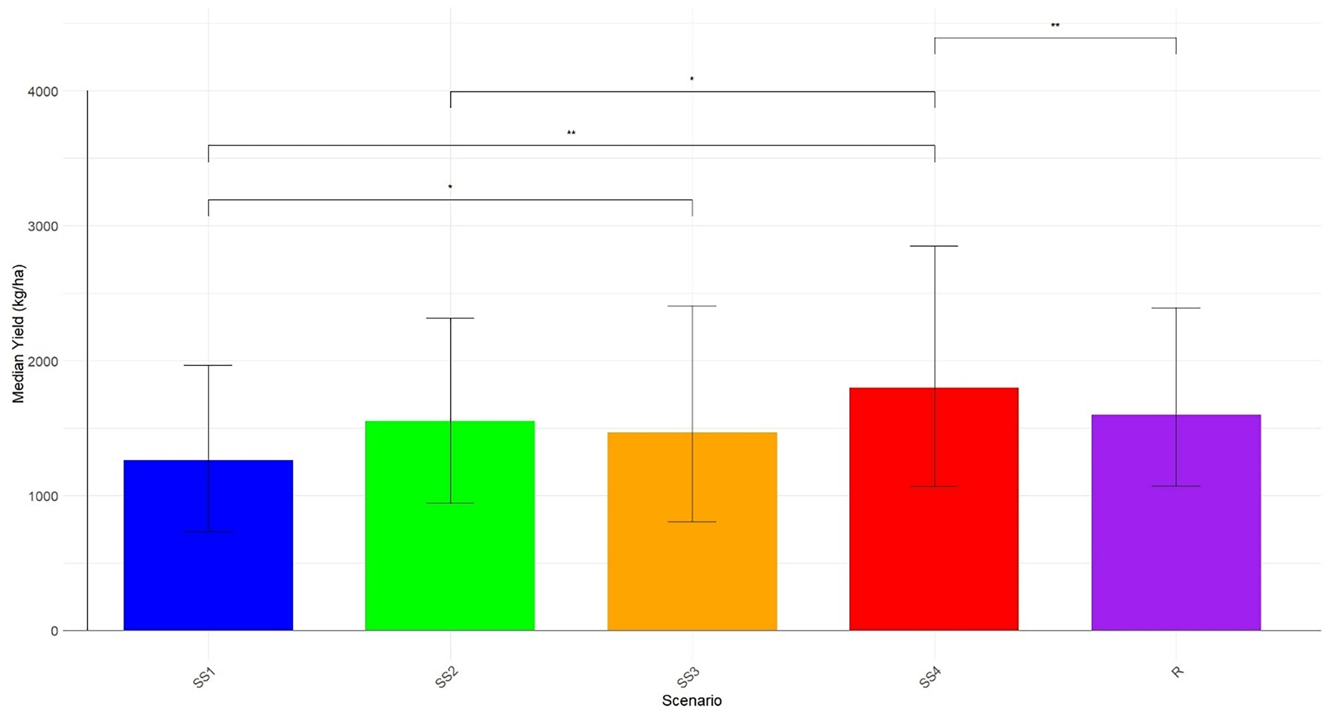

FIGURE 3 | Barplot of scenario simulations (SS1–SS4) and reported (*R*) yields (kg/ha) across the North West Province for data between 1981 and 1999. Horizontal lines above the bars indicate statistically significant pairwise differences where a single asterisk (*) indicates significance at $p < 0.05$ and a double asterisk (**) indicates significance at $p < 0.01$.

Given the observed distributional differences among scenarios, the Fligner–Killeen test was applied and indicated significant heterogeneity of variance across scenarios ($p < 0.05$). Pairwise differences in yield variability were subsequently assessed using Wilcoxon rank-sum tests applied to absolute deviations. Significant differences in variability were detected between SS1 and SS3 ($p < 0.05$) and between SS1 and SS4 ($p < 0.01$). SS2 also differed significantly from SS4 ($p < 0.05$). When compared with reported yields, only SS4 exhibited a statistically significant difference in variability ($p < 0.01$), whereas SS1, SS2 and SS3 did not differ significantly from the reported data (Figure 3).

3.2 | District Level

The descriptive statistics for each individual district and simulation scenario can be found in Table S2. No significant trends ($p < 0.05$) were exhibited in any of the district yield data from 1981 to 1999. Kolmogorov–Smirnov (K–S) tests comparing simulated and reported yield distributions at the district level indicated limited distributional differences across the NWP (Table 7). Schweizer–Reneke was the only district where significant differences were observed for three scenario simulations (SS1–SS3; $p < 0.05$). In all other districts, none of the scenario simulations differed significantly from reported yields, indicating broadly consistent distributional behaviour across scenarios.

Spearman rank correlation analysis showed moderate to very strong agreement between simulated and reported inter-annual yield variability across districts for SS2 (Figure 4a). Correlation coefficients ranged from 0.68 in Klerksdorp to 0.90 in Vryburg. Across districts, SS2 recorded the highest or near-highest correlation coefficients relative to the other scenario simulations. WLS regression further demonstrated variation in model agreement at the district scale (Figure 4b). Adjusted R^2 values ranged from 0.49 in Schweizer–Reneke to 0.77 in Coligny across all scenarios, indicating moderate to high levels of explained variance. Schweizer–Reneke was the only district where adjusted R^2 values consistently remained below the commonly applied threshold for satisfactory agreement (adjusted $R^2 < 0.60$). Overall, SS2 produced the highest adjusted R^2 values across districts, indicating more consistent agreement with reported yields relative to the other scenarios.

District-level evaluation metrics (Table S3) further highlighted differences in model performance across scenarios. While several districts exhibited acceptable agreement under multiple scenarios, SS2 more frequently achieved lower error magnitudes (RMSE and nRMSE), higher efficiency (NSE) and stronger goodness-of-fit (adjusted R^2 and *d*) across districts. Other scenarios displayed greater variability in performance across metrics and districts. To synthesise these results, individual evaluation metrics were aggregated into a criterion-based summary of acceptable performance (Table S4). This synthesis confirms that SS2 satisfied the greatest number of evaluation criteria across districts, achieving five or more acceptable metrics in most cases. In districts including Coligny, Delareyville, Koster, Lichtenburg, Marico, Ventersdorp, Vryburg and Wolmaransstad, SS2 met at least six of the seven criteria ($\geq 85\%$ satisfactory agreement). By contrast, SS3 and SS4 frequently met fewer than four criteria, particularly in Schweizer–Reneke, Swartruggens and Rustenburg, indicating reduced robustness when evaluated across multiple

TABLE 7 | Kolmogorov–Smirnov test significance results for each district comparing Scenario Simulations and reported yields. Differences were considered statistically significant at $p < 0.05$.

District	SS1 *p*-value	SS2 *p*-value	SS3 *p*-value	SS4 *p*-value
Bloemhof	0.30	0.80	0.52	0.98
Christiana	0.54	0.97	0.80	0.98
Coligny	0.15	0.31	0.98	0.81
Delareyville	0.15	0.31	0.31	0.54
Klerksdorp	0.54	0.98	0.81	0.81
Koster	0.54	0.80	0.81	0.31
Lichtenburg	0.07	0.15	0.31	0.81
Marico	0.54	0.81	0.81	0.98
Potchefstroom	0.81	0.81	0.54	0.15
Rustenburg	0.54	0.81	0.98	0.15
Schweizer–Reneke	< 0.05*	< 0.05*	< 0.05*	0.30
Swartruggens	0.15	0.81	0.98	0.15
Ventersdorp	0.98	0.98	0.98	0.30
Vryburg	0.54	0.81	0.81	0.54
Wolmaransstad	0.07	0.31	0.15	0.81

*Significance difference at a level of 0.05.

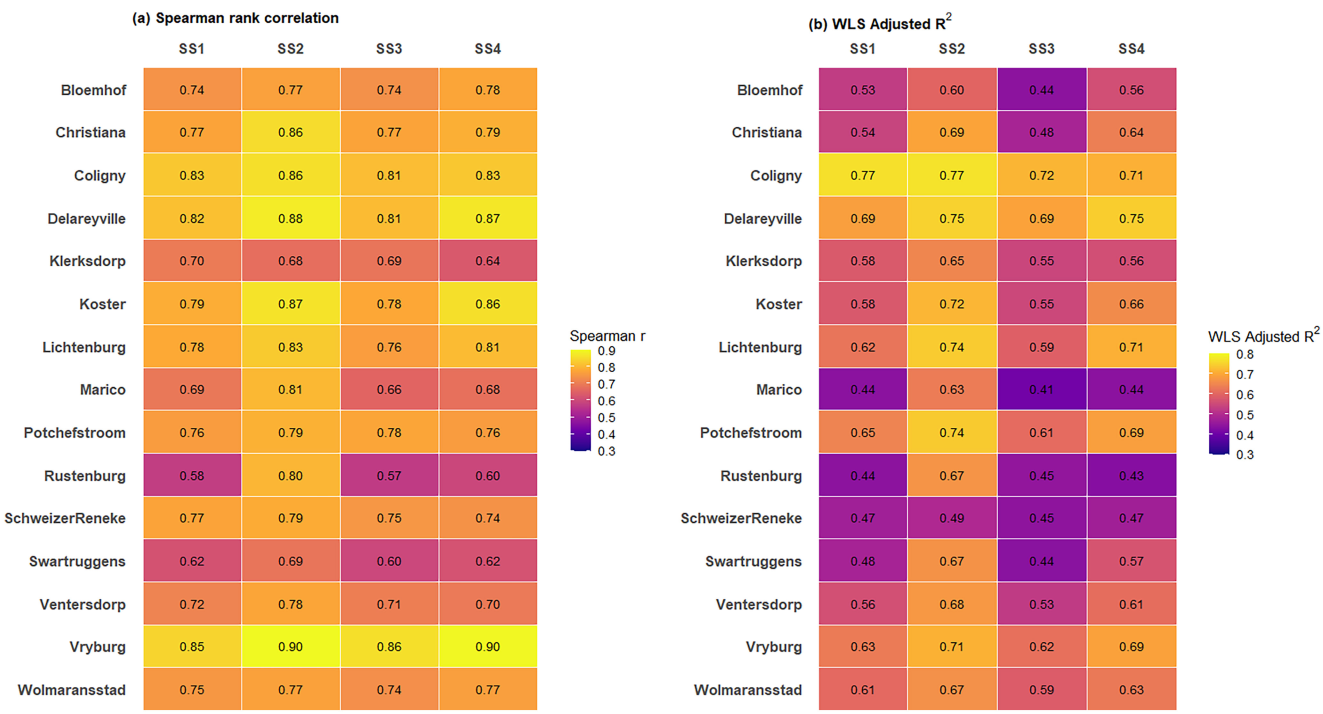

FIGURE 4 | District level evaluation of DSSAT maize yield simulations across four scenario simulations (SS1—SS4). (a) Spearman rank correlation coefficients (r) indicating agreement of inter-annual yield variability. (b) WLS adjusted R^2 values indicating the proportion of variance explained between simulated and reported yields.

complementary measures. While isolated metrics occasionally favoured alternative scenarios, for example, SS4 achieving full criterion satisfaction in Delareyville. The aggregated assessment identifies SS2 as the most reliable configuration when accuracy, error magnitude, bias, efficiency and goodness-of-fit are considered jointly.

A Kruskal–Wallis test was applied to assess differences in median yields between reported data and scenario simulations for each district over the 1981–1999 period (Figure 5). No significant differences in medians were detected for any district ($p > 0.05$), indicating that simulated yields across all scenarios reproduced the central tendency of reported yields at the district scale (Table S5).

Pairwise comparisons of yield medians among districts revealed significant spatial differences for both reported and simulated

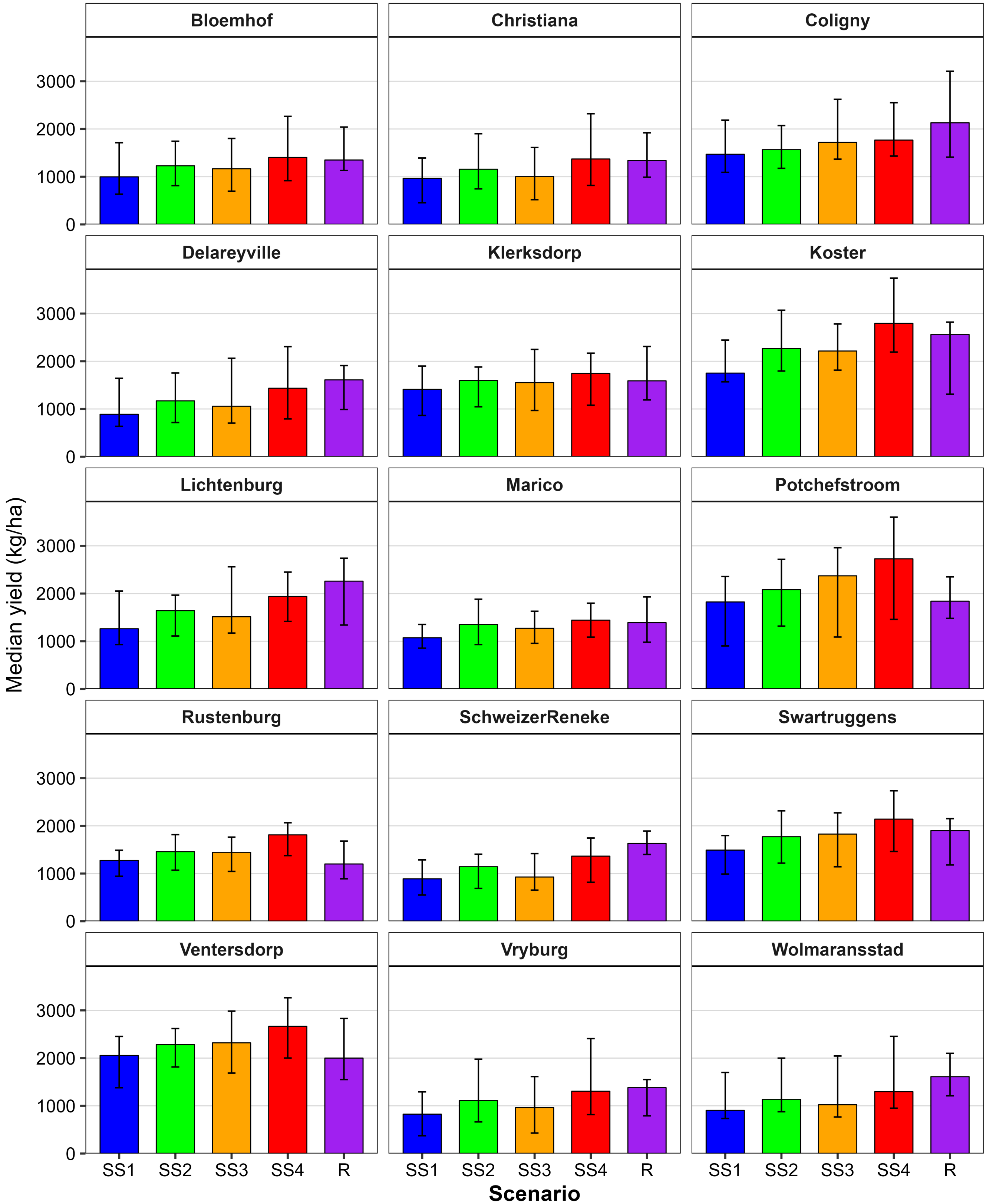

FIGURE 5 | Boxplot of scenario simulations (S1–S4) and reported (*R*) yields (kg/ha) per district for data between 1981 and 1999.

yields ($p < 0.05$). Of the 105 possible district comparisons, reported yields showed significant differences in 26 cases, while scenario simulations exhibited between 28 and 31 significant differences (Table S6). This indicates that spatial variability in yield is preserved across both reported and simulated datasets.

4 | Discussion

Process-based crop models such as DSSAT are widely used to evaluate crop responses to climatic variability and management practices, yet their performance is known to be sensitive to both spatial scale and parameterisation choices (Challinor et al. 2004; Boote et al. 2011). A central objective of this study was to assess how scenario configuration and spatial resolution influence the agreement between simulated and reported maize yields in the NWP. The findings provide several insights into the strengths and limitations of DSSAT when applied under rainfed, spatially heterogeneous conditions.

The absence of significant monotonic trends in both reported and simulated yields aligns with previous studies indicating that maize yield variability in semi-arid regions of southern Africa is primarily driven by inter-annual climate variability rather than long-term technological or management trends (Ray et al. 2015; Müller et al. 2017). This reinforces the appropriateness of focusing on distributional characteristics and inter-annual variability rather than trend detection when evaluating model performance over relatively short historical periods.

Scenario-based differences in yield variability highlight the sensitivity of DSSAT to cultivar selection, soil depth and initial soil water content. Similar sensitivities have been reported in previous DSSAT evaluations, where cultivar parameterisation was shown to strongly influence phenological development, water stress responses and final yield outcomes (Jones et al. 2003; Boote et al. 2011). In this study, scenarios retaining the PAN6479 cultivar generally reproduced reported yield variability more effectively than those incorporating the ZM521 cultivar, suggesting that cultivar-specific calibration plays a critical role in regional yield simulations. The comparatively weaker performance of SS4 indicates that simultaneous modification of cultivar and soil parameters may amplify yield variability beyond that observed under prevailing production systems, particularly when climatic constraints dominate crop growth.

The influence of spatial scale was a key finding of this study. Provincial-level aggregation of simulated yields produced reliable estimations of yield as in Huffman et al. (2015), which aggregated simulated crop yields on individual soils at a regional scale. However, in this study aggregating yields to a provincial level resulted in fewer scenarios reproducing reported yield distributions, whereas district-level analyses revealed generally stronger agreement. This outcome is consistent with earlier work demonstrating that spatial aggregation can obscure local variability in soil properties, management practices and climate, thereby reducing the apparent skill of crop models at broader scales (Lobell et al. 2009; Bassu et al. 2014). The emergence of Schweizer–Reneke as an outlier district, where multiple scenarios differed significantly from reported yields, further underscores the importance of localised environmental or management factors that may not be fully captured by uniform model parameterisation.

Evaluation using multiple performance metrics revealed that no single metric adequately described model behaviour across all districts, supporting the growing consensus that multi-criteria evaluation frameworks are essential for robust crop model assessment (Willmott et al. 1985; Bennett et al. 2013). Relative error measures such as RMSE and nRMSE were elevated in several districts, which is consistent with previous DSSAT applications in southern Africa, where high climate-driven yield variability inflates error statistics (Zinyengere et al. 2015). In contrast, the generally high index of agreement and moderate-to-strong correlation coefficients indicate that DSSAT was able to reproduce inter-annual yield variability despite larger absolute errors.

The finding that simulated and reported yield medians did not differ significantly at the district level has important implications. It suggests that DSSAT effectively captures the central tendency of maize yields across diverse environments, even though year-to-year variability and error magnitudes vary spatially. Similar behaviour has been reported in other regional DSSAT evaluations, where median or mean yields were reproduced satisfactorily despite limitations in simulating extreme yield outcomes (Corbeels et al. 2016; Attia et al. 2021). This pattern implies that DSSAT may be more responsive to dominant climatic drivers, such as rainfall and temperature variability, than to non-climatic stressors such as pests, weeds or nutrient limitations, which are implicitly reflected in reported yields (Challinor et al. 2009) but not explicitly represented in the model.

Finally, the persistence of spatial variability in yield medians across districts for both reported and simulated data highlights the necessity of spatially explicit model evaluation. Differences among districts likely reflect interacting effects of soil depth, cultivar response, planting conditions and local climate regimes, as documented in previous studies of maize production systems in water-limited environments (Van Ittersum et al. 2013; Lobell et al. 2014). These findings reinforce the importance of incorporating spatial heterogeneity into crop model calibration and validation frameworks to enhance confidence in both historical assessments and future climate impact applications.

5 | Conclusion

Previous studies have commonly applied process-based crop models to assess maize yield responses to climate variability at regional or global scales, while validation at finer administrative levels has remained limited. This study addressed this gap by evaluating the spatial performance of DSSAT maize yield simulations at both provincial and district levels across the North West Province of South Africa. The results demonstrate that DSSAT is capable of reproducing inter-annual yield variability across spatial scales, with stronger agreement generally observed at the district level, highlighting the importance of spatial resolution in crop model evaluation.

Scenario-based analyses revealed that model performance was sensitive to assumptions regarding cultivar selection, soil depth and initial soil water content, with SS2 consistently emerging as the most robust configuration across multiple evaluation criteria. While aggregation at the provincial scale provides a useful representation for policy-level applications, district-level analyses revealed spatial variability in model performance that would otherwise be obscured, underscoring the value of finer-scale evaluation for locally relevant decision-making.

Although no significant differences were observed between simulated and reported yield medians at the district level, variation in error metrics and efficiency measures indicates that DSSAT performance is influenced more strongly by climatic variability than by non-climatic factors under the rainfed conditions of the North West Province. The contrasting behaviour of evaluation metrics further highlights the necessity of applying multi-criteria assessment frameworks when evaluating crop model performance. Overall, this study demonstrates that spatially explicit, scenario-based crop modelling can enhance confidence in yield simulations and support more informed agricultural planning and climate adaptation strategies in water-limited environments.

Author Contributions

Christopher James Rankin: conceptualization, methodology, visualization, project administration, formal analysis, writing – original draft, data curation. **Trevor Lumsden:** conceptualization, methodology, data acquisition, reviewing. **Shingirai S. Nangombe:** conceptualization, data analysis, reviewing. **Willem Landman:** data analysis, visualization, supervision. **Asmerom Beraki:** funding acquistion, conceptualization, reviewing. **Mohau Mateyisi:** conceptualization, methodology, data anlysis, supervision, reviewing.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Data S1:** met70172-sup-0001-Supplementary_Tables.docx.