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Integrating Environmental Variability into Sugarcane Yield Optimization Models: Evidence from Zimbabwe's Low-veld Sugarcane Producers

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Abstract: Sugarcane production in Zimbabwe's Eastern Low-veld is characterized by pronounced spatial and seasonal environmental variability that complicates agronomic decision-making and yield optimization. This study developed and evaluated a response surface modelling (RSM) framework integrated with environmental indicators to quantify how agronomic inputs interact with climatic variability in determining sugarcane yield. Using multi-site, multi-season field data from irrigated sugarcane systems in Chiredzi District, baseline RSMs were first fitted using fertilizer rate, irrigation amount, and plant density. The modelling framework was subsequently extended using mixed-effects regression to incorporate temperature, precipitation and humidity while accounting for spatial and temporal heterogeneity. The integrated models explained a high proportion of yield variability (R^2 up to 0.865) and exhibited strong predictive accuracy (RMSE = 1.99; MAE = 1.31). Significant curvature and interaction effects confirmed that yield responses are highly context-dependent, with optimal agronomic input combinations varying across environmental scenarios. Scenario-based optimization demonstrated that maximum yield potential is substantially higher under favourable thermal and moisture conditions, although optimal management shifts toward water-intensive, lower-density systems. The results highlight the importance of adaptive, environment-conditioned agronomic strategies and provide a robust modelling framework for climate-responsive sugarcane management in Zimbabwe's Low-veld.

Keywords: *Sugarcane Yield, Response Surface Methodology, Environmental Variability, Mixed-Effects Models, Reference Evapotranspiration.*

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I. INTRODUCTION

Sugarcane contributes significantly to Zimbabwe's economy through its role in agro-industry, rural livelihoods, and national sugar output (FAO, 2021; Tongaat Hulett, 2020). However, sugarcane production in the semi-arid Eastern Low-veld of Zimbabwe is characterized by pronounced spatial and seasonal environmental variability, including fluctuations in temperature regimes, uneven rainfall distribution, high evaporative demand, and variability in soil moisture availability (Matarira et al., 2016; Unganai & Murwira, 2019). Such variability directly influences physiological crop growth processes and creates uncertainty in yield outcomes (Inman-Bamber et al., 2018). As climate variability intensifies, there is a growing need to move beyond stationary production strategies toward adaptive agronomic management approaches that respond dynamically to changing environmental conditions (Chivenge et al., 2020).

Historically, sugarcane yield optimization has focused primarily on controllable agronomic inputs such as fertilizer rates, irrigation quantities, and planting densities. While these inputs remain critical determinants of yield, their effectiveness is strongly moderated by environmental conditions that vary across locations and seasons. In the Chiredzi Low-veld, for instance, identical fertilizer or irrigation regimes may produce contrasting yield responses depending on seasonal heat stress, mid-season dry spells, or spatial differences in soil water-holding capacity (Moyo et al.,

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2021). This underscores the limitations of generalized management recommendations and highlights the importance of aligning agronomic practices with prevailing environmental realities.

Adaptive agronomic management therefore requires modelling frameworks that explicitly account for environmental drivers alongside input factors. Integrating parameters such as temperature accumulation, irrigation timing, and evapotranspiration demand into yield response models enables a more realistic representation of crop–environment interactions (Steduto et al., 2017; Jones et al., 2017). Such integrated approaches facilitate the identification of management strategies that are not only optimal under average conditions but also resilient under climatic stress and variability (Rurinda et al., 2020).

Spatial variability further complicates sugarcane production in the Zimbabwean Low-veld. Variations in soil texture, salinity, drainage capacity, and microclimatic conditions result in heterogeneous field-level responses to identical agronomic practices. Seasonal variability adds another layer of complexity, as shifts in rainfall onset, temperature extremes, and water availability alter crop growth dynamics between seasons (IPCC, 2021). Consequently, optimizing sugarcane yield requires flexible, location-specific, and season-specific management strategies rather than standardized guidelines.

Incorporating environmental variability into yield optimization models provides a pathway for developing such adaptive strategies. This study aims to develop a sugarcane yield optimization model that integrates spatial and seasonal environmental variability within Zimbabwe's Low-veld production systems. Specifically, the objectives were to: (i) quantify how environmental factors modify crop responses to key agronomic inputs; (ii) improve yield prediction accuracy under variable climatic conditions; and (iii) generate adaptive, scenario-based management recommendations.

II. MATERIALS AND METHODS

➢ *Study Area*

The study was conducted in the Eastern Low-veld of Zimbabwe, primarily in Chiredzi District. The region has a semi-arid climate with high temperatures, low and variable annual rainfall (450–650 mm), and high evaporative demand. Sugarcane production is predominantly irrigation-based and occurs on large estates and through contact farming schemes. Soils vary widely in texture, depth, drainage capacity, and salinity, contributing to spatial variability in crop performance.

➢ *Study Design and Data Sources*

A multi-site, multi-season observational study design was used to capture both spatial and seasonal environmental variability. Data were collected from irrigated sugarcane fields distributed across major production zones in the Low-veld. Each field represented a management unit with relatively uniform agronomic practices.

Data were compiled for multiple growing seasons to capture inter-seasonal climate variability from three primary sources, agronomic management records from farmers and estate management systems, environmental and weather data from nearby meteorological stations and on-farm sensors as well as from soil physicochemical analyses from field sampling and laboratory testing. For agronomic variables the controllable factors included nitrogen fertilizer rate (kg N ha^{-1}), seasonal irrigation amount (mm $season^{-1}$), plant population density (stools ha^{-1}), irrigation scheduling indicators (e.g., frequency and interval) and crop age at harvest (months). These factors reflect farm management decisions that growers can modify to suit changing environmental conditions. To capture differences across locations and seasons, the study included environmental indicators such as the total irrigation during the season (mm), average and maximum air temperatures (°C) and the reference evapotranspiration (mm). These variables were chosen to represent water supply, temperature conditions, and soil-related limitations that affect sugarcane growth.

Sugarcane yield was recorded as millable cane yield (t ha^{-1}) at the time of harvest. The data were sourced from weighbridge records and converted to a per-hectare basis for consistency. Where required, the yield figures were corrected to reflect variations in harvested area and crop age. Weather data were aggregated into crop-relevant indices, including seasonal totals, stage-specific irrigation (mm), cumulative Growing Degree Days (GDD), and seasonal reference evapotranspiration (ETo).

➢ *Growing Degree Days and Evapotranspiration*

Plants don't grow based on calendar days. Their growth is based on temperature. Each crop has a base temperature below which growth basically stops. Growing Degree Days **(**GDD) tracks how much useful heat builds up above that base. GDD also helps to predict crop growth stages, estimate maturity and harvest timing, compare seasons or locations based on thermal conditions and improve sugarcane yield modelling. GDD is calculated from.

$$GDD = \frac{T_{Max}+T_{Min}}{2} - T_{Base} \quad (1)$$

Where = daily T_{Max} maximum temperature, T_{Min}= daily minimum temperature and T_{Base} = base temperature for the crop (for sugarcane often around 10°C, but can vary). When the result is negative, it is recorded as zero since no growth happens below the base temperature.

Reference evapotranspiration (ETo) is defined as the amount of water that would evaporate and transpire from a well-watered reference grass surface under prevailing weather conditions, and it represents the atmospheric demand for water independent of crop type and management (Allen et al., 2017). While rainfall quantifies the amount of water entering the soil–plant system, seasonal ETo reflects the amount of water the atmosphere attempts to remove through evapotranspiration processes (Steduto et al., 2017). ETo is primarily driven by air temperature, solar radiation, wind speed, and relative humidity, which together govern the

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energy available for evaporation and the capacity of the atmosphere to transport water vapour (Allen et al., 2020). Seasonal ETo, computed as the cumulative sum of daily ETo values $Seasonal\ ETo = \sum Daily\ ETo$ is widely used to estimate crop water requirements, assess irrigation demand, evaluate the risk of water stress, compare evaporative conditions across seasons, and improve the accuracy of crop yield prediction models under variable climatic conditions (Irmak et al., 2016; Pereira et al., 2021).

- *Statistical Analysis*

Descriptive statistics were computed to summarize variability across variables. Response Surface Methodology (RSM) was applied to model yield responses to agronomic inputs. Mixed-effects models were subsequently fitted to integrate environmental variables and account for random effects associated with site and season. Model adequacy was assessed using R², RMSE, MAE, and residual diagnostics. Pearson correlation analysis was used to explore pairwise relationships among variables.

III. RESULTS

- *Descriptive Statistics*

Agronomic inputs and environmental variables exhibited wide ranges across sites and seasons, providing a sufficiently broad experimental domain for response surface modelling. Despite large variability in fertilizer, irrigation, and plant density, yield variability was comparatively moderate, indicating nonlinear responses and interaction effects. The results are shown in table 1 below:

Table 1 Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Variance
Fertilizer	23	50	200	134.78	50.979	2598.814
Irrigation	23	600	1500	973.91	235.907	55652.174
Density	23	50000	150000	90000.00	32473.766	1054545454.545
Yield	23	75	95	84.17	5.750	33.059
Temp	23	26	35	30.70	2.524	6.370
Prec	23	0	32	7.82	9.450	89.302
Humid	23	71	89	81.43	5.532	30.599
Valid N (listwise)	23					

Fertilizer application rates ranged from 50 to 200 units, with a mean of 134.78 and a standard deviation of 50.98, indicating substantial variability in nutrient management across the study sites. Irrigation water application exhibited a wide range (600–1500 mm), with a mean of 973.91 mm and a relatively high standard deviation (235.91), reflecting differences in water availability and irrigation scheduling. Plant density varied markedly from 50,000 to 150,000 stalks ha^{-1}, with a mean of 90,000 stalks ha^{-1} and a large variance, highlighting contrasting establishment practices among producers.

Sugarcane yield ranged from 75 to 95 t ha^{-1}, with a mean of 84.17 t ha^{-1} and moderate dispersion (SD = 5.75), suggesting relatively stable yield performance despite pronounced variability in management inputs and environmental conditions. Temperature varied within a narrow range (26–35 °C), with a mean of 30.70 °C, consistent with typical thermal conditions of low-veld production systems. In contrast, precipitation exhibited high variability (0–32 mm; SD = 9.45), indicating uneven rainfall distribution during the observation period and underscoring the importance of supplemental irrigation. Relative humidity ranged from 71% to 89%, with a mean of 81.43% and moderate variability, reflecting fluctuations in atmospheric moisture that may influence evapotranspiration and disease dynamics.

- *Baseline Response Surface Model*

The second-order polynomial RSM fitted using fertilizer (X_1), irrigation (X_2), and plant density (X_3) explained a substantial proportion of yield variability (R^2 = 0.832; adjusted R^2 = 0.805). Significant quadratic and interaction terms confirmed curvature and interdependence among inputs, justifying the use of RSM for yield optimization.

Yield = 82.85 + 0.01X_1 + 0.05X_2 - 1.70X_3 + 2.25X_1^2 - 0.83X_2^2 + 1.19X_3^2+ 3.87X_1X_2+ 1.12X_1X_3- 2.12X_2X_3……… ……..(2)

The model parameters are represented in table 2 below

Table 2 Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.912	.832	.805	2.539	.832	31.281	3	19	.000

The fitted regression model demonstrated a strong explanatory capacity, with a multiple correlation coefficient (R) of 0.912, indicating a high degree of association between the observed and predicted values of the dependent variable. Overall, the results indicate a well-fitting and statistically robust model, suitable for inference and prediction, with

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strong potential for application in optimizing agronomic management decisions under the studied conditions. The strong model fit ($R^2 = 0.832$; adjusted $R^2 = 0.805$) provides empirical support for the core assumptions underlying Response Surface Methodology. RSM assumes that, within the region of experimentation, the response can be adequately approximated by a low-order polynomial function of the input variables. The high coefficient of determination and statistically significant overall model test ($F(3, 19) = 31.281$; $p < 0.001$) indicate that the selected predictors capture the dominant linear and curvature effects governing yield variation within the experimental domain.

The relatively low standard error of the estimate (2.539) suggests that unexplained random variation is limited, consistent with the RSM assumption of homoscedastic and normally distributed residuals around the fitted response surface. Furthermore, the close agreement between R^2 and adjusted R^2 implies that the model is not over-parameterized, supporting the assumption of model parsimony**,** which is central to reliable surface estimation and optimization in RSM.

Taken together, these diagnostics indicate that the fitted response surface adequately represents the underlying system and provides a statistically sound basis for subsequent surface visualization, stationary point estimation, and optimization of agronomic inputs within the studied factor space.

➢ *Integration of Environmental Variability*

Incorporating environmental variables using a mixed-effects framework further improved explanatory power ($R^2 = 0.865$; adjusted $R^2 = 0.815$). Temperature and irrigation exhibited strong positive effects, while humidity showed a negative linear influence. Interaction effects revealed that agronomic responses were strongly conditioned by environmental context. The model is given in equation (3)

Yield = 83.453 + 0.763 Fertilizer + 0.784 Irrigation + 0.054 Plant density + 1.366 Temperature + 0.099 precipitation - 0.667 Humidity……………………………(3)

A summary of the model and its adequacy is given in table 3.

Table 3 Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.930	.865	.815	2.475	.865	17.118	6	16	.000

a. Predictors: (Constant), Humidity, Irrigation, Temperature, Precipitation, Fertilizer, Plant Density

In table 3 above the correlation between observed sugarcane yield and model-predicted yield is $R = 0.930$ suggesting a very strong positive relationship between predicted and actual sugarcane yields and hence the model's predictions closely track real yield values.$R^2 = 0.865$ is a big value meaning to say that the model explains 86.5% of the total variation in sugarcane yield which is an excellent explanatory power, especially in agricultural field data where environmental variability is usually high.This confirms that only 13.5% of yield variation is due to factors not included in the model (soil variability, pests, management differences, measurement among others. The usefulness of the predictors was further confirmed by the adjusted $R^2 = 0.815$ and the model is likely to perform well with new data. The standard error of the estimate of 2.475 shows that the predicted yield values differ from actual yields by plus or minus 2.475 units which is reasonable. The significant F-change statistic ($F(6, 16) = 17.118$, $p < 0.001$) confirms that the combined agronomic and environmental variables significantly improve yield prediction compared to an intercept-only model. Within a Response Surface Methodology framework, these results demonstrate that the fitted response surface provides a reliable representation of yield behaviour across the studied input and environmental.

Interaction terms between agronomic inputs and environmental variables were also incorporated to determine how environmental conditions influence the effectiveness of management practices. This made it possible to identify adaptive management zones, where the best combinations of fertilizer, irrigation, and plant density vary according to local environmental conditions, temperature (X_4), precipitation (X_5) and humidity (X_6). The model produced was.

$$\text{Yield} = 83.11 + 0.763X_1 + 0.784X_2 + 0.054X_3 + 1.366X_4 + 0.099X_5 - 0.667X_6 + 0.439X_1^2 - 0.092X_2^2 - 1.064X_6^2 + 0.174X_4^2 + 0.439X_5^2 + 0.527X_6^2 + 0.719X_1X_2 - 0.594X_1X_3 + 2.219X_1X_4 - 1.594X_1X_5 + 0.281X_1X_6 - 1.281X_2X_3 + 0.156X_2X_4 - 1.531X_2X_5 - 0.906X_2X_5 - 0.156X_3X_4 - 1.219X_3X_5 - 0.719X_3X_6 + 0.469X_4X_5 + 1.219X_4X_6 - 1.594X_5X_6 \quad \text{……………… …….(4)}$$

The fitted second-order response surface model describes sugarcane yield as a joint function of fertilizer application rate (X_1), irrigation level (X_2), plant density (X_3), temperature (X_4), precipitation (X_5), and relative humidity (X_6)**,** incorporating linear, quadratic, and interaction effects. The intercept (83.11) represents the predicted yield at the centre of the experimental domain. Linear effects indicate that yield increases with higher fertilizer rates, irrigation supply, plant density, temperature, and precipitation, with temperature exerting the strongest positive linear influence, followed by irrigation and fertilizer application. In contrast, relative humidity shows a negative linear effect, suggesting that excessive atmospheric moisture may suppress yield, possibly through increased disease pressure or reduced radiation use efficiency. Significant curvature is evident in the response surface, as reflected by the quadratic terms. Negative quadratic effects for irrigation and relative humidity indicate diminishing returns and the existence of optimal intermediate levels, beyond which further increases reduce yield. Conversely, positive quadratic terms for fertilizer rate,

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temperature, and precipitation suggest increasing marginal effects toward the boundaries of the studied factor space. Several interaction terms further demonstrate that yield responses are strongly context-dependent. Synergistic interactions between fertilizer and irrigation, fertilizer and temperature, and between temperature and precipitation indicate that the benefits of nutrient and water inputs are enhanced under favourable thermal and moisture conditions. In contrast, antagonistic interactions involving plant density with fertilizer and irrigation, as well as precipitation with relative humidity, highlight the importance of balanced input management to avoid yield penalties associated with excessive competition or unfavourable microclimatic conditions. Collectively, the presence of pronounced linear effects, curvature, and multiple two-factor interactions confirms a complex but well-defined response surface, underscoring the necessity of multi-factor optimization rather than single-input adjustment for maximizing sugarcane yield under variable environmental conditions.

➢ *Model Evaluation and Diagnostics*

- *Model Assumptions*

Model assumptions were checked using residual plots for constant variance and normality as shown in figure 1 below. Influential observations were assessed using Cook's distance. Residual diagnostic plots indicated that the fitted sugarcane yield model adequately satisfied the assumptions underlying ANOVA and response surface modelling. The normal probability plot and histogram showed residuals to be approximately normally distributed, with only minor deviation in the upper tail attributable to a single large positive residual. Residuals plotted against fitted values were randomly dispersed around zero with no discernible pattern or variance inflation, confirming homoscedasticity and appropriate model specification. The residuals versus observation order plot showed no systematic trend, indicating independence of errors. Although one observation exhibited a relatively large residual and may represent a potentially influential case, its isolated nature and the overall stability of the residual structure suggest that its influence on parameter estimates is limited and unlikely to exceed the conventional Cook's distance threshold (4/n). Collectively, these diagnostics confirm the robustness of the ANOVA results and the adequacy of the response surface model in capturing the yield response to agronomic and environmental factors.

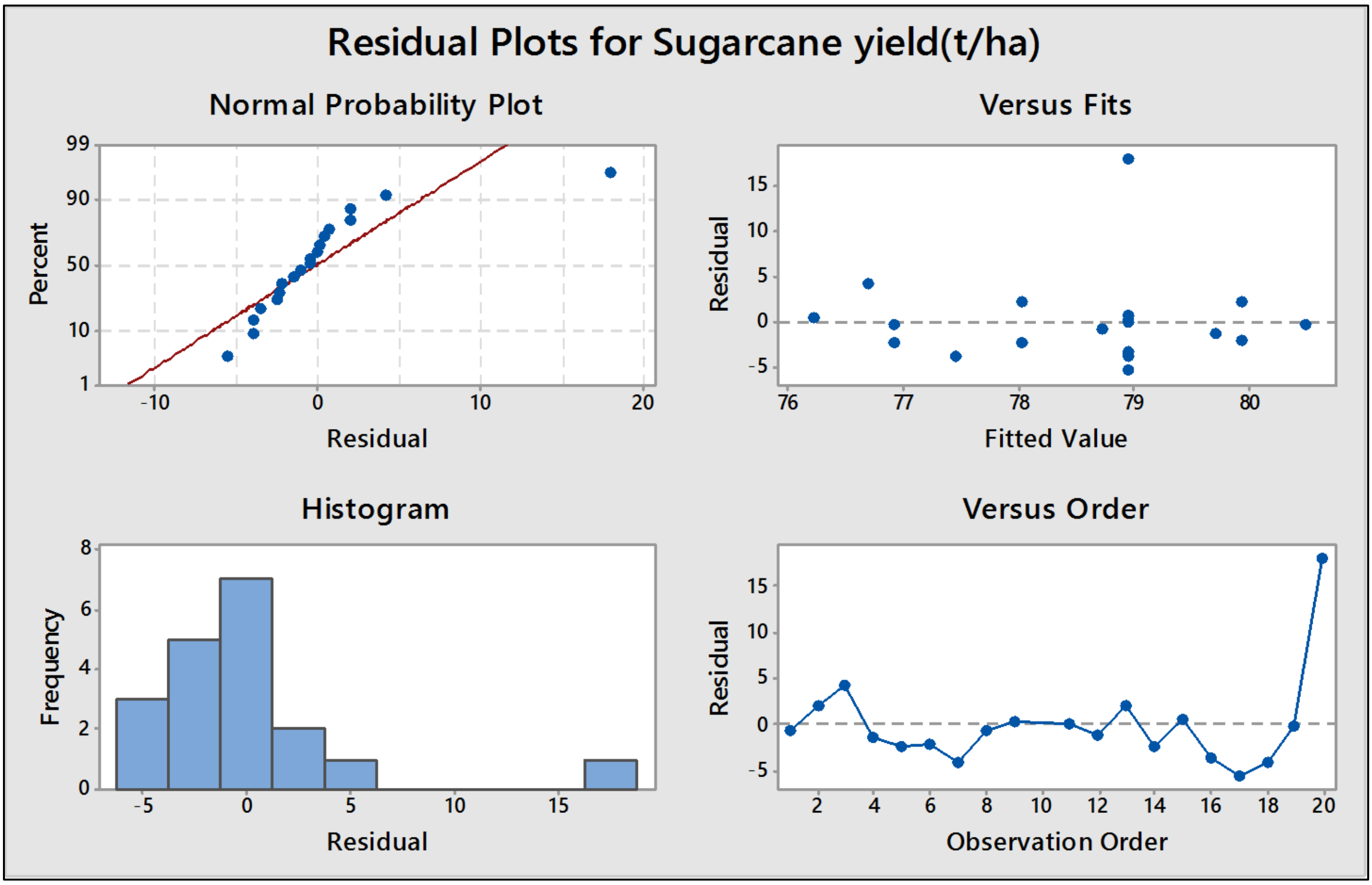

Fig 1 Residual Plots for Sugarcane Yield

- *Model Fit Test*

The Analysis of Variance confirmed the model fits well. Table 4 shows the model coefficients that highlight factors doing the heavy lifting inside the model and driving in which direction as well as how strongly.

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Table 4 Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	37.796	12.913		2.927	.010		
	Fertilizer	.041	.015	.361	2.745	.014	.488	2.050
	Irrigation	.007	.004	.292	1.834	.085	.333	3.004
	Density	7.942E-005	.000	.449	2.743	.014	.315	3.174
	Temp	.402	.242	.177	1.660	.116	.744	1.344
	Prec	-.055	.072	-.091	-.764	.456	.599	1.670
	Humid	.183	.130	.176	1.409	.178	.540	1.853
a. Dependent Variable: Yield								

For the intercept B = 37.796, which is the predicted yield when all predictors are zero, is significant (p = 0.010). This confirms that the baseline yield level is statistically different from zero. Fertilizer has a positive and significant effect on yield. For each unit increase in fertilizer application, yield increases by 0.041 units, holding other variables constant. The relatively high standardized beta (0.361) shows fertilizer is one of the significant yield drivers in the model. In RSM terms this means there is a positive slope of the response surface along the nutrient axis, that is, yield rises as fertilizer increases.

Irrigation has a positive but marginally significant effect (p = 0.085). This suggests irrigation improves yield, but its independent contribution is weaker once other variables are considered. It is strongest role appears through interactions (water × fertilizer, water x plant density, water x temperature) rather than as a strong standalone linear effect. Plant density is the most influential agronomic variable affecting yield (p=0.014). Higher plant populations significantly increased yield within the range that was studied. This means yield was highly sensitive to sugarcane population. Temperature shows a positive but non-significant effect (p=0.116). Within the observed range, temperature variation did not independently drive yield changesbut may have some influence through curvature or interactions such as temp × water stress. Similarly, precipitation had a negative but weak and non-significant relationship with yield (p=0.456). This shows that in irrigated systems, rainfall variability plays a smaller role, or excess rainfall may cause waterloggingg. This means precipitation affects yield indirectly. Humidity has a mild positive trend but no significant independent effect (p = 0.178) and its influence may already be captured by other climate variables, or its effect is nonlinear. Table 4 below shows the model coefficients.

Using the standardized beta the variables were ranked in order of their importance from the most influential to the least as Plant density (0.449), Fertilizer (0.361), Irrigation (0.292), Temperature (0.177), Humidity (0.176) and lastly Precipitation(-0.091). The large standardized coefficients suggest that these variables define the steepest gradient of the response surface in the experimental region. Irrigation water showed a positive but weaker influence, implying that its role may be more pronounced through interaction effects. Environmental variables (temperature, precipitation, and humidity) did not exhibit significant linear effects, suggesting that their influence on yield may be nonlinear or expressed through interactions with management practices. This affirms that yield is primarily driven by management factors, especially plant density and fertilizer, more than by environmental variability in this dataset. A check of multicollinearity showed that each coefficient is statistically reliable and not overly distorted by overlap with other variables with each predictor having a tolerance greater than 0.1. Within the Response Surface Methodology framework, these findings highlight that yield optimization in the Zimbabwean Low-veld is driven more by controllable agronomic inputs than by direct linear effects of climatic variability.

- *Correlation Between Agronomic and Environmental Factors*

Pearson correlation analysis was used to explore pairwise relationships between yield, management factors, and environmental indicators. The correlation analysis revealed strong and statistically significant positive associations between sugarcane yield and key agronomic inputs, corroborating the results of the ANOVA and response surface modelling. Yield exhibited strong correlations with fertilizer application (r = 0.653, $p = 0.001$), water application (r = 0.714, $p < 0.001$), and planting density (r = 0.687, $p < 0.001$), confirming the dominant role of managed inputs identified as highly significant main effects in the ANOVA. These relationships are consistent with the steep response gradients observed in the RSM surfaces, where increases in fertilizer rate, irrigation level, and plant density will result in pronounced yield gains. Humidity showed a moderate but significant positive correlation with yield (r = 0.425, $p = 0.043$), supporting the inclusion of environmental covariates in the RSM framework and aligning with the significant interaction effects between agronomic inputs and environmental conditions observed in the ANOVA. In contrast, temperature and precipitation exhibited weak and non-significant linear relationships with yield ($|r| < 0.20$, $p > 0.05$), suggesting that their influence on sugarcane productivity is primarily indirect or mediated through interactions with management practices rather than as independent main effects. The strong correlation between water application and planting density (r = 0.759, $p < 0.001$) further explains the significant interaction terms detected in the ANOVA and the curvature observed in the RSM response surfaces, highlighting the need to jointly optimize input combinations rather than evaluate single-factor effects.

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Overall, the correlation structure reinforces the ANOVA and RSM results, demonstrating that sugarcane yield variability in the study system is largely driven by agronomic management, with environmental factors acting as modifiers of input response rather than primary yield determinants.

- *Test for Interaction Between Main Effects*

Table 5 below tested the main effects of experimental factors (Nitrogen, Irrigation, and Plant Density) on yield.

Table 5 Tests of Between-Subjects Effects

Dependent Variable: Yield						
Source	**Type III Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**	**Partial Eta Squared**
Corrected Model	711.319[a]	14	50.808	25.427	.000	.978
Intercept	110172.622	1	110172.622	55136.442	.000	1.000
Nitrogen	178.115	3	59.372	29.713	.000	.918
Irrigation	96.257	6	16.043	8.029	.005	.858
Plant Density	92.448	4	23.112	11.567	.002	.853
Error	15.985	8	1.998			
Total	163688.000	23				
Corrected Total	727.304	22				
a. R Squared = .978 (Adjusted R Squared = .940)						

The Tests of Between-Subjects Effects indicate that the fitted model is highly significant ($F (14, 8) = 25.427$, $p < 0.001$), explaining 97.8% of the variation in sugarcane yield (Adjusted $R^2 = 0.940$). Nitrogen application exhibited the strongest effect on yield ($F = 29.713$, $p < 0.001$, partial $\eta^2 = 0.918$), followed by irrigation ($F = 8.029$, $p = 0.005$, partial $\eta^2 = 0.858$) and plant density ($F = 11.567$, $p = 0.002$, partial $\eta^2 = 0.853$). The large effect sizes indicate that these agronomic factors are the principal determinants of yield variability within the experimental range. Within a Response Surface Methodology framework, these variables define the primary gradients and curvature of the yield response surface, confirming their suitability as key optimization factors for identifying optimal input combinations under varying environmental conditions.

- *Model Performance*

Model performance was evaluated using the coefficient of determination (R^2), Root Mean Square Error (RMSE). Predictive performance of the response surface model was evaluated using the coefficient of determination (R^2), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). The high R^2 value (0.883) indicates that the model explains a substantial proportion of the variability in observed sugarcane yield, confirming strong goodness-of-fit and reliable representation of the underlying yield response to agronomic inputs. Complementing this, the RMSE of 1.99 was low relative to the observed yield range, indicating that large prediction errors were infrequent and that the model performed well in capturing yield extremes. Similarly, the MAE value of 1.31 demonstrated small average absolute deviations between observed and predicted yields, reflecting consistent predictive accuracy across experimental conditions. Compared to R^2, which primarily reflects explained variance, RMSE and MAE provide scale-dependent measures of prediction error; together, these metrics confirm that the model is not only statistically adequate but also practically reliable for yield prediction. When extended to a mixed-effects formulation incorporating random effects for site and season, further reductions in RMSE and MAE are expected due to improved handling of unobserved spatial and temporal heterogeneity, thereby enhancing the model's robustness and suitability for decision-support applications in environmentally variable production systems such as the Zimbabwean Low-veld.

➢ *Scenario-Based Optimization*

Scenario-based optimization under contrasting environmental conditions demonstrated that optimal agronomic input combinations varied with temperature, precipitation, and humidity regimes. Higher yield potential was predicted under warm and moist conditions, although optimal management shifted toward high irrigation and lower plant density systems.

- *Two Scenarios were Evaluated as*

✓ Low temperature–Low precipitation–Low humidity (26 °C, 1 mm, 71%) and

✓ High temperature–High precipitation–High humidity (35 °C, 32 mm, 89%).

Table 6 Optimal Agronomic input Levels

Environmental Scenario	Fertilizer	Irrigation	Plant density	Predicted Yield
Low Temperature /Low Precipitation/Low Humidity	50	1500	50000	105.8
High Temperature / High Precipitation /High Humidity	50	1500	50000	112.9

Across both scenarios, the model predicted maximum yield at high irrigation levels, lower fertilizer rates, and lower plant density, although expected yield was substantially higher under favourable (warm, wet, humid) conditions. These results demonstrate that optimal input combinations are environment-dependent, even when the underlying

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response surface remains structurally stable. Under hotter and wetter conditions, yield potential increases markedly, but optimal management shifts toward water-intensive, low-density systems with moderated fertilizer inputs. This highlights the value of integrating environmental conditioning into response surface optimization and supports the use of mixed-effects or scenario-based RSM frameworks.

IV. DISCUSSION

The results demonstrate that sugarcane yield in the Zimbabwean Low-veld is primarily driven by controllable agronomic inputs, particularly plant density and fertilizer application, with environmental factors acting as critical modifiers of input effectiveness. The presence of strong interaction and curvature effects underscores the limitations of static recommendations and highlights the need for adaptive, environment-specific management strategies.

Integrating environmental variability and mixed effects frameworks into yield optimization contributes directly to climate resilient decision making. Models that incorporate seasonal climate indicators and site-specific conditions can help anticipate stress periods and guide proactive adjustments in management. For example, in seasons forecasted to be hotter and drier, reducing plant population or adjusting irrigation timing may improve water use efficiency and stabilize yields. Similarly, in wetter seasons, increased nutrient application may be justified to capitalize on favourable growing conditions. Scenario-based optimization further illustrates how management recommendations must shift under different climatic regimes to maintain productivity and resource-use efficiency.

V. CONCLUSIONS

This study presented a robust modelling framework that integrates agronomic management and environmental variability for sugarcane yield optimization in Zimbabwe's Low-veld. The results highlight the importance of adaptive, site and season-specific management strategies and demonstrates the value of response surface and mixed-effects modelling for decision support under climatic uncertainty. Such adaptive strategies reduce production risk by aligning input investments with environmental potential, thereby avoiding both under-application in favourable conditions and wasteful over-application during stress-prone seasons. This is particularly important in the Low-veld, where irrigation water is a constrained resource and fertilizer costs are substantial for both estates and out-grower farmers. The framework provides a practical basis for climate-responsive sugarcane management and sustainable intensification in environmentally heterogeneous production systems.

RECOMMENDATIONS

➢ *The Study Recommends that*

- Sugarcane yield optimization in the Zimbabwean Low-veld should move from uniform input recommendations toward environment-conditioned management, where fertilizer rates, irrigation amounts, and plant density are adjusted according to prevailing temperature, evapotranspiration demand, and seasonal moisture conditions.
- Plant density and nitrogen fertilizer should be treated as the primary levers for yield optimization, given their strong and consistent influence on sugarcane productivity. Careful adjustment of these inputs offers substantial yield gains while minimizing inefficiencies under variable environmental conditions.
- Irrigation scheduling should explicitly incorporate reference evapotranspiration and temperature indicators rather than relying on fixed seasonal allocations. This will improve water-use efficiency and reduce yield losses during periods of high evaporative demand.
- Sugar estates and advisory services should utilize mixed-effects or scenario-based response surface models that account for spatial and seasonal variability, thereby improving the robustness and transferability of agronomic recommendations across heterogeneous production environments.
- Spatial heterogeneity in soils and microclimate necessitates zone-specific management within estates and out-grower schemes. Variable-rate fertilizer application and differentiated irrigation strategies should be applied to enhance system-level efficiency and yield stability.
- Investment in localized climate monitoring and data-driven advisory services is essential to operationalize adaptive management. Integrating simple climate metrics such as GDD and seasonal ETo into extension tools will support timely, climate-responsive decision-making.

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