MODELING RELATIONSHIPS BETWEEN GRAIN YIELD AND TRAITS IN PEARL MILLET

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SUMMARY

This research paper investigates the complex relationships influencing pearl millet yield using Structural Equation Modeling (SEM). The study employed data from pearl millet genotypes, encompassing various yield components and attributing traits. Principal Component Analysis (PCA) was utilized to identify latent variables representing dimensions related to yield determination. A recursive SEM with latent variables was constructed, incorporating measurement models for exogenous and endogenous variables and a structural model depicting causal relationships. Maximum likelihood estimation was used to estimate model parameters, and goodness-of-fit criteria were applied for model evaluation. The study revealed fertility's pivotal role in determining pearl millet yield, with tillering capacity and panicle weight identified as crucial factors. Physiological and morphological traits also influenced yield but to a lesser extent, indicating a complex interplay of factors. The final SEM model provided valuable insights into these dynamics, highlighting the intricate relationships and pathways involved in yield determination.

Key word: Pearl millet, yield determination, Structural Equation Modeling (SEM), Principal Component Analysis (PCA), latent Variables, exogenous variables, endogenous variables, fertility, tillering capacity, panicle weight

In the agricultural domain, particularly in agrarian nations like India, the cultivation of pearl millet (*Pennisetum glaucum* (L.) R. Br.), commonly referred to as bajra, holds significant importance due to its role in employment generation and contribution to the Gross Domestic Product (GDP). This crop, primarily cultivated during the *Kharif* (rainy) season, is a staple food for millions, especially in arid regions, and serves as crucial feed and fodder for livestock. Major pearl millet producers include Rajasthan, Maharashtra, Gujarat, Uttar Pradesh, and Haryana, which collectively account for over 90% of the country's pearl millet cultivation. During the 2018-19 season, India's pearl millet cultivation spanned 6.8 million hectares, yielding 8.5 million tonnes with a productivity rate of 1236 kg/ha. Notably, Haryana alone cultivated pearl millet on 0.42 million hectares, yielding 0.88 million tonnes at a productivity rate of 2068 kg/ha. Pearl millet thrives as a drought-tolerant crop in dry and warm climates characterized by low annual rainfall ranging from 40 cm to 60 cm. The optimal temperature for its growth falls between 20°C to 30°C, with moist conditions during its vegetative phase being particularly beneficial. However, it is sensitive to acidic and water-logged soil conditions.

The growth and development of pearl millet involve a complex, non-linear process influenced by numerous factors, with grain yield being a key trait shaped by morpho-physiological processes impacted by both direct (genetic, physiological, biological) and indirect (habitat, cultivation practices) factors. These factors significantly contribute to estimating grain yield per plant. Previous studies have predominantly utilized traditional quantitative genetic methodologies such as correlation, path analysis, and heritability estimation to explore the interplay between yield and yield-contributing traits in pearl millet (Singh *et al.,* 2015; Omar & Hag, 2015; Ezeaku *et al*., 2015; Rani, 2019; Pallavi *et al*., 2020; Patil *et al.,* 2021; Kumar *et al*., 2022; Madankar *et al*., 2023). While these approaches provide valuable insights into trait genetics and their relationships, they have inherent limitations viz, correlation analysis only identifies associations between traits without establishing causal links. Path analysis aids in delineating direct and indirect effects but relies on assumptions regarding trait causal structures. Moreover, heritability estimates may vary due to environmental factors and could lack consistency across different populations and environments. Several studies have employed multivariate analyses like principal component analysis (PCA) and cluster analysis to evaluate genetic diversity and genotype relationships (Ramya *et al*., 2017; Madankar *et al*., 2023), which facilitate the visualization of intricate datasets and the identification of key traits contributing to variability but necessitate cautious interpretation and consideration of underlying assumptions.

Despite the insights offered by traditional quantitative genetic methods such as correlation, path analysis, and heritability estimation, their limitations, including the inability to establish causal relationships and potential inconsistencies in heritability estimates across populations and environments, are noteworthy. Multivariate analyses like PCA and cluster analysis have aided in assessing genetic diversity and genotype relationships but demand careful interpretation.

Structural Equation Modeling (SEM) emerges as a robust tool to address these limitations, allowing researchers to construct and test models representing hypothesized causal relationships among observed variables and latent constructs. This approach facilitates the disentanglement of direct and indirect effects, providing a nuanced understanding of how various factors contribute to outcomes such as grain yield in pearl millet. SEM can also accommodate measurement errors and latent variables, which are often present but not directly observable in biological systems.

In agricultural research, structural equation modeling (SEM) has become a potent tool, offering a sophisticated approach to unravel the intricate relationships between crop yield and its contributing factors. Early proponents like Lamb *et al*. (2011) recognized SEM's value in crop analysis, favorably comparing it to traditional multivariate techniques such as PCA and cluster analysis. Subsequent researchers have utilized SEM to explore various aspects of crop production and yield, including identifying diverse genotypes for hybridization programs in pearl millet (Kumar *et al*., 2015) and understanding genetic divergence within pearl millet germplasm (Verma *et al*., 2016). Other studies have delved into relationships between grain yield and contributing traits in barley (Niwas et al., 2021), connections between agronomic characteristics and yield in winter wheat (Zheng et al., 2017), the influence of soil properties on wheat yield components (Nazmi, 2013), and factors affecting yield in Canadian flax (Zhang et al., 2014). These varied applications underscore SEM's versatility and effectiveness in elucidating crop yield determinants across species and environmental contexts. Given SEM's wide applicability in studying yield and its attributing characteristics, this study aims to delineate the causal relationship between grain yield and various components using SEM in pearl millet genotypes.

MATERIALS AND METHODS

This study utilizes secondary data from a previous experiment conducted at CCS Haryana Agricultural University. Fifty genotypes of pearl millet were evaluated during the Kharif season of 2017-2018 at the Bajra Research Area of the Department of Genetics and Plant Breeding. The data encompasses various yield components and attributing traits, including days to 50% flowering, days to maturity, plant height, panicle length and diameter, number of total and productive tillers per plant, panicle weight, grain yield, 1000-seed weight, biological yield, and harvest index.

To analyze the relationships between these variables, a structural equation model (SEM) was developed. The initial step involved employing principal component analysis (PCA) as a factor analysis method to identify underlying factors contributing to yield and its related traits. Based on the significant factor loadings, latent variables were established by empirically grouping the exogenous and endogenous variables. Each latent variable, representing a specific dimension or factor, was then further tested using maximum likelihood confirmatory factor analysis. This process guided the conceptualization and development of the structural equation model.

A recursive SEM with latent variables was formulated to capture the intricate relationships among the analyzed variables. This model incorporated both measurement models for exogenous and endogenous latent variables, as well as a structural model depicting the causal relationships between them. The measurement models expressed the observed variables as functions of the latent variables and measurement errors, while the structural model defined the relationships between the latent variables themselves.

The measurement model for each dimension in the form of standard factor analytical model is given by

$$y = ?y\, \eta + \varepsilon \qquad \text{...(1)}$$

for latent endogenous variables with $E(\varepsilon\varepsilon') = \Theta_\varepsilon$ and

$$x = ?_x \xi + \delta \qquad \text{...(2)}$$

for latent exogenous variables with $E(\delta\delta') = \Theta_\delta$ We also define $E(\varepsilon\delta') = \Theta_{\delta\varepsilon}$ and $E(\xi\xi') = \Theta$, where

- **y** is a *p x 1* vector of observed indicators of the dependent (endogenous) latent variable $\boldsymbol{\eta}$
- **x** is a *q x 1* vector of observed indicators of the independent (exogenous) latent variables ξ
- η is a *m x 1* random vector of latent dependent or endogenous variables
- ξ is a *n x 1* random vector of latent independent or exogenous variables
- ε is a *p x 1* vector of measurement error in **y**
- δ_y is a *q x 1* vector of measurement error in **x**
- Λ_y is a *p x m* matrix of coefficients of regression of **y** on **?** and
- Λ_x is a *q x n* matrix of coefficients of regression of x on ξ

The implied covariance/correlation matrix $\boldsymbol{\Sigma(\theta)}$ is given by E(xx') or E(yy') for measurement models with the assumptions

$$E(\mathbf{x}) = E(\boldsymbol{\delta}) = 0 \text{ and } E(\boldsymbol{\xi\delta'}) = E(\boldsymbol{\delta\xi'}) = 0, \text{ then}$$

$$\therefore \Sigma(\theta) = \Lambda_x \Phi \Lambda'_x + \Theta_\delta \quad ...(3)$$

Then the structural part of the model is given by

$$\eta = B\eta + \Gamma\xi + \zeta \quad ...(4)$$

We also define E $(\xi\xi) + \psi$, where

- B is a *m x m* coefficient matrix that relates endogenous variables to each other
- Γ is a *m x n* coefficient matrix that relates endogenous variables to exogenous variables and ξ is a *m x 1* vector of errors (residuals)

Maximum likelihood estimation was employed to estimate the model parameters, and the model's goodness-of-fit was evaluated using multiple criteria such as chi-square, goodness-of-fit index (GFI), and standardized root mean square residual (SRMR). Initially, a restricted model was tested with certain assumptions about the error terms. However, this model did not fit the data well. Therefore, the model was refined by relaxing restrictions on the error terms' correlation matrices based on modification indices. This led to a final model with improved fit statistics, indicating its suitability for representing the relationships between yield and its attributing traits in the studied pearl millet genotypes.

The final SEM revealed a complex network of relationships, with physiological, morphological, and fertility parameters influencing grain yield directly and indirectly. The model allowed for a deeper understanding of the causal pathways involved in yield formation and provided valuable insights into the relative importance of different traits.

RESULTS AND DISCUSSION

For the purpose of developing structural equation models, ten yield and its components were identified and the description of these attributes has been presented in Table 1.

TABLE 1
Codes and description of the variables of pearl millet genotypes

Code	Description	Symbols
DF	Days to 50% flowering	x_1
DM	Days to maturity	x_2
PH	Plant height	x_3
PL	Panicle length	x_4
PD	Panicle Diameter	x_5
TTP	Number of total tillers per plant	x_6
PTP	Number of productive tillers plant	x_7
PW	Panicle weight	x_8
GYP	Grain Yield	y_1
TGW	1000 seed weight	y_2
BYP	Biological yield	y_3
HI	Harvest index	y_4

The development of a structural equation model for pearl millet crop data was grounded in the identification of four latent variables, as derived from preliminary exploratory factor analysis. The initial model encountered challenges in achieving an optimal solution. To enhance model fit, adjustments were made by relaxing certain restrictions, such as modifying the elements of residual matrices and adjusting the inclusion of indicator variables within the latent variables, based on the guidance provided by the largest modification indices. Following these adjustments, the model parameters were recalculated, leading to a model that successfully converged to an optimal solution with satisfactory fit statistics.

This finalized structural equation model revealed a non-trivial structure within the data, highlighting the intricate relationships between latent variables and their error terms associated with yield-determining characteristics. The factor analysis uncovered four key factors essential for influencing grain yield and other yield-related attributes. Among these latent variables, physiological parameters (ξ_1), morphological parameters (ξ_2), and fertility parameters (ξ_3) were identified as exogenous, while yield parameters (η_1) were classified as endogenous.

Initially, a basic recursive structural equation model was constructed, incorporating these four latent variables based on the structure suggested by the exploratory factor analysis of pearl millet grain yield. Subsequently, the model parameters were estimated using the maximum likelihood method, and the model's goodness of fit was assessed. This approach not only identified the complex relationships among the latent variables and their error terms but also provided a structured framework for understanding the various components that contribute to yield, from plant growth and development to fertility and productivity.

The exogenous measurement model, as defined by equation (2), is represented by the matrix equation (5) below:

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \\ x_7 \\ x_8 \end{bmatrix} = \begin{bmatrix} \lambda_{11}^{(x)} & 0 & 0 \\ \lambda_{21}^{(x)} & 0 & 0 \\ 0 & \lambda_{32}^{(x)} & 0 \\ 0 & \lambda_{42}^{(x)} & 0 \\ 0 & \lambda_{52}^{(x)} & 0 \\ 0 & 0 & \lambda_{63}^{(x)} \\ 0 & 0 & \lambda_{73}^{(x)} \\ 0 & 0 & \lambda_{83}^{(x)} \end{bmatrix} \begin{bmatrix} \xi_1 \\ \xi_2 \\ \xi_3 \end{bmatrix} + \begin{bmatrix} \delta_1 \\ \delta_2 \\ \delta_3 \\ \delta_4 \\ x\delta_5 \\ \delta_6 \\ \delta_7 \\ \delta_8 \end{bmatrix} \quad ...(5)$$

Equation (5) illustrates those three exogenous latent variables (ξ_1), (ξ_2), and (ξ_3) are measured by a range of indicators related to grain yield parameters. Specifically, (ξ_1), representing physiological parameters, is assessed through indicators such as days to 50% flowering (DF) with an estimated factor loading of 0.23, indicating a weaker influence of flowering time, alongside days to maturity (DM), which exhibits high positive factor loadings of 0.87, showing a strong positive influence of the maturity period on this factor (Table 2). The second latent variable, (ξ_2), encompassing morphological parameters, shows significant positive loadings on indicators like plant height (PH), panicle length (PL), and panicle diameter (PD). For instance, plant height (PH) has an estimated factor loading of 3.64 on (ξ_2), indicating a significant positive influence on morphological parameters, although with a high standard error of 11.98, suggesting uncertainty in this relationship. Panicle length (PL) has an estimated factor loading of 0.76 on (ξ_2), with a standard error of 0.15, indicating a significant positive influence on morphological parameters. Lastly, (ξ_3), concerning fertility parameters, is positively associated with indicators including total tillers per plant (TTP), number of productive tillers per plant (PTP), and panicle weight (PW). Total tillers per plant (TTP) have an estimated factor loading of 0.68 on (ξ_3), with a standard error of 0.13, indicating a positive influence on fertility parameters.

In contrast, the endogenous measurement model, formulated using equation (2), is designed to capture the relationship between these exogenous variables and the endogenous latent variable, which represents the grain yield parameters. The endogenous measurement model using (1) has been formulated as:

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \end{bmatrix} = \begin{bmatrix} \lambda_{11}^{(y)} \\ \lambda_{21}^{(y)} \\ \lambda_{31}^{(y)} \\ \lambda_{41}^{(y)} \end{bmatrix} [\square_1] + \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \epsilon_3 \\ \epsilon_4 \end{bmatrix} \quad ...(6)$$

It has been observed from parameter estimates presented in table 2, the yield parameters (η_1) are influenced by various indicators, as shown by their factor loadings. Grain yield per plot (GYP) has a very high factor loading of 0.94 on (η_1), indicating a highly significant and strong positive influence on overall yield. Similarly, 1000 seed weight (TGW) also has a very high factor loading of 0.95 on (η_1), indicating a very significant positive influence. Biological yield per plot (BYP) has a factor loading of 0.98 on (η_1), showing a strong but slightly uncertain positive influence, as indicated by its standard error of 0.39. Lastly, harvest index (HI) has a factor loading of 0.53 on (η_1), indicating a moderate but significant positive influence, with a standard error of 0.11.

The structural equation model has been formulated by using (4) and is as given below:

$$\eta_1 = \gamma_{11}\xi_1 + \gamma_{21}\xi_2 + \gamma_{31}\xi_3 + \gamma_{41}\xi_4 + \zeta_1 \quad ...(7)$$

where the latent error terms have the following covariance matrix

$$\psi = \mathrm{var}(\zeta_1) \qquad ...(8)$$

The path diagrams for final model which fits well to the data and the relationship between yield and its components for pearl millet crop with estimated coefficients has been presented in Fig. 1.

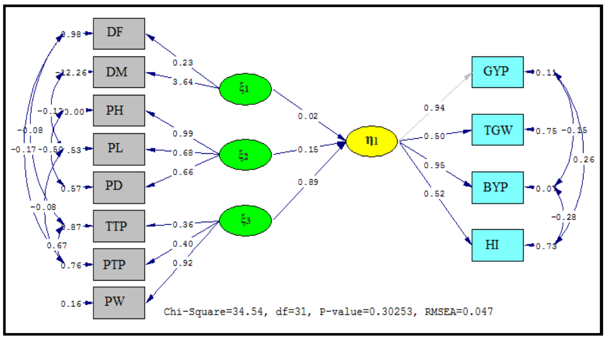

Fig. 1. Path diagram for model of pearl millet to establish relationship between yield and its components with coefficient estimates.

Fig. 1 illustrates the influence of the exogenous latent variables, specifically the physiological and morphological parameters, with path coefficients of 0.02 and 0.15 respectively, indicating a positive impact on the endogenous latent variable. The third exogenous latent variable, fertility parameters, has a significant positive path coefficient to the endogenous latent variable, with a standardized regression weight of 0.89. Additionally, there is a positive and significant correlation coefficient between the exogenous latent variables ξ_1 and ξ_2.

The model parameters were estimated using the maximum likelihood technique, employing two distinct residual correlation matrix specifications. Initially, the restricted model was assessed by setting the off-diagonal elements of θ_δ, θ_ε and $\theta_{\delta\varepsilon}$ to zero. The Chi-square value for the restricted model was calculated as 538.64 (d.f. = 66), with a Goodness of Fit Index (GFI) of 0.90 and a Standardized Root Mean Square Residual (SRMR) of 0.097. These metrics suggest that the model did not adequately fit the data.

To enhance the model's fit, the zero restrictions on the off-diagonal elements in the correlation matrices of error terms were relaxed. This adjustment was based on the identification of error terms that were significantly correlated, as determined by standardized residual and modification indices. By removing the zero restriction on several off-diagonal elements of θ_δ, θ_ε and $\theta_{\delta\varepsilon}$ as detailed in equations (9),

$$\Theta_\delta = \begin{bmatrix} \theta_{11}^{\delta} & & & & & & & \\ 0 & \theta_{22}^{\delta} & & & & & & \\ 0 & 0 & \theta_{33}^{\delta} & & & & & \\ 0 & \theta_{42}^{\delta} & 0 & \theta_{44}^{\delta} & & & & \\ 0 & 0 & \theta_{53}^{\delta} & 0 & \theta_{55}^{\delta} & & & \\ \theta_{61}^{\delta} & 0 & 0 & 0 & 0 & \theta_{66}^{\delta} & & \\ \theta_{71}^{\delta} & 0 & 0 & \theta_{74}^{\delta} & 0 & \theta_{76}^{\delta} & \theta_{77}^{\delta} & \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \theta_{88}^{\delta} \end{bmatrix} \qquad ...(9)$$

$$\Theta_\epsilon = \begin{bmatrix} \theta_{11}^{\epsilon} & & & \\ 0 & \theta_{22}^{\epsilon} & & \\ \theta_{31}^{\epsilon} & 0 & \theta_{33}^{\epsilon} & \\ \theta_{41}^{\epsilon} & 0 & \theta_{43}^{\epsilon} & \theta_{44}^{\epsilon} \end{bmatrix} \qquad ...(10)$$

$$\Theta_{\delta\epsilon} = \begin{bmatrix} \theta_{11}^{\delta\epsilon} & 0 & 0 & 0 \\ \theta_{21}^{\delta\epsilon} & 0 & 0 & \theta_{24}^{\delta\epsilon} \\ \theta_{31}^{\delta\epsilon} & 0 & \theta_{33}^{\delta\epsilon} & \theta_{34}^{\delta\epsilon} \\ 0 & 0 & 0 & \theta_{44}^{\delta\epsilon} \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & \theta_{72}^{\delta\epsilon} & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \qquad ...(11)$$

(10), and (11), the model's Chi-square value improved to 34.54 (d.f. = 31), with a GFI of 0.96 and an SRMR of 0.047. These results indicate a better fit for establishing the relationship between yield and its components for the pearl millet crop in Haryana state. The final model parameters, including their estimates and standard errors, are detailed in Table 2. This table reveals that the estimated factor loadings are statistically significant at the 5 percent level of significance. The data in Table 2 indicates that the exogenous variable ξ_1 exerts a positive influence on the endogenous latent variable η_1. Furthermore, the exogenous latent variables ξ_2 and ξ_3 demonstrate a significantly positive influence on η_1. Additionally, there

TABLE 2

Maximum likelihood estimates for structural equation model for pearl millet crop in Haryana

Parameter	Estimate (S.E.)	Standardized Estimates	Parameter	Estimate (S.E.)	Standardized Estimates
$\lambda^{(x)}_{11}$	0.23 (0.76)	0.23	θ^{δ}_{66}	0.87 (0.17)	0.87
$\lambda^{(x)}_{21}$	3.64 (11.98)	3.60	θ^{δ}_{77}	0.76 (0.15)	0.83
$\lambda^{(x)}_{31}$	0.99 (0.13)	1.00	θ^{δ}_{88}	0.16 (0.11)	0.16
$\lambda^{(x)}_{42}$	0.68 (0.13)	0.68	θ^{δ}_{42}	-0.12 (0.05)	-0.11
$\lambda^{(x)}_{52}$	0.66 (0.14)	0.66	θ^{δ}_{53}	-0.50 (0.12)	-0.50
$\lambda^{(x)}_{63}$	0.36 (0.14)	0.36	θ^{δ}_{61}	-0.08 (0.07)	-0.08
$\lambda^{(x)}_{73}$	0.40 (0.13)	0.42	θ^{δ}_{71}	-0.17 (0.07)	-0.18
$\lambda^{(x)}_{83}$	0.92 (0.12)	0.92	θ^{δ}_{74}	-0.08 (0.04)	-0.08
$\lambda^{(x)}_{11}$	0.94 (0.00)	0.94	θ^{δ}_{76}	0.67 (0.15)	0.70
$\lambda^{(x)}_{21}$	0.50 (0.13)	0.50	θ^{δ}_{11}	0.11 (0.08)	0.11
$\lambda^{(x)}_{31}$	0.95 (0.11)	0.96	θ^{δ}_{12}	0.75 (0.14)	0.75
$\lambda^{(x)}_{41}$	0.52 (0.10)	0.52	θ^{δ}_{33}	0.07 (0.08)	0.08
γ_{11}	0.02 (0.08)	0.02	θ^{δ}_{44}	0.73 (0.15)	0.73
γ_{12}	0.15 (0.15)	0.15	θ^{δ}_{31}	-0.15 (0.08)	-0.16
γ_{13}	0.89 (0.17)	0.89	θ^{δ}_{41}	0.26 (0.08)	0.26
ϕ_{21}	-0.04 (0.15)	-	θ^{δ}_{43}	-0.28 (0.07)	-0.28
ϕ_{31}	-0.02 (0.08)	-	θ^{δ}_{11}	-0.07 (0.04)	-0.07
ϕ_{32}	0.64 (0.11)	-	θ^{δ}_{21}	-0.15 (0.06)	-0.14
var(?$_1$)	0.02 (0.12)	0.02	θ^{δ}_{24}	-0.13 (0.07)	-0.13
θ^{δ}_{11}	0.98 (0.39)	0.95	θ^{δ}_{31}	-0.06 (0.06)	-0.06
θ^{δ}_{22}	-12.26 (87.35)	-11.98	θ^{δ}_{33}	-0.16 (0.06)	-0.16
θ^{δ}_{33}	0.00 (0.18)	0.00	θ^{δ}_{34}	0.18 (0.08)	0.19
θ^{δ}_{44}	0.53 (0.11)	0.54	θ^{δ}_{44}	0.12 (0.05)	0.12
θ^{δ}_{55}	0.57 (0.15)	0.57	θ^{δ}_{72}	0.12 (0.06)	0.12
?_((df=31))^2			34.54	(P=0.30253)	
GFI			0.96		
SRMR			0.047		

is a positive correlation between the exogenous latent variables ξ_2 and ξ_3.

SUMMARY AND CONCLUSIONS

The Structural Equation Model (SEM) proves superior to traditional path analysis in unravelling the relationships between pearl millet yield and its contributing traits. It's a effective method for exploring into the internal connections among various variables, both observed and latent, shedding light on complex interactions. The study focused on fertility's pivotal role in determining yield, particularly highlighting tillering capacity and panicle weight as crucial factors. While physiological and morphological traits also influence yield, their impact is nuanced, indicating a multifaceted relationship between different aspects of plant growth. The SEM model, refined through our analysis, offers valuable insights into these dynamics, though it's worth noting that other factors not explored in our study may also contribute to yield variability. Future research could expand this model by incorporating weather and soil parameters, potentially employing a Bayesian approach for comparison.

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